University Technology Transfer and Research Portfolio Management

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Abstract

University technology transfer is of critical importance to the U.S. innovation economy. Understanding the drivers of technology transfer efficiency will shed light on University research portfolio management. In this dissertation, survey data from The Association of University Technology Managers is analyzed in various aspects to offer a overall understanding of the technology transfer industry, which include University research fund composition, technology transfer office staffing, licenses executed to start-ups, small companies, and large companies, license income composition, legal fee expenditures, new patents applications, provisional patents, utility patents, and non USA patents, invention disclosures, U.S. patents issued, start-ups initiated, and annual averages of U.S. University technology transfer offices.

Then, a two-stage technology transfer model based on Data Envelopment Analysis is proposed to address the limitation of the single-stage model. The two-stage model provides the capacity to evaluate the efficiencies of university research and technology transfer office separately and also as a whole, offering better insights for university technology transfer management. Year to year productivity changes are also measured using Malmquist Index. It is found the productivity growth has stemmed primarily from a growth in commercialization by all universities rather than a catching up by the inefficient universities. Finally, technology transfer efficiency and academic reputation is studied for the first time. Counter intuitively, they are not correlated.

To further understand University research portfolio management, Modern Portfolio Theory is applied for the first time in this field. University disciplines are categorized into three major disciplines: engineering, physical and mathematical sciences, and biological and life sciences. The risk and return of technology transfer are defined and research portfolio risk-return curve are solved. Then correlation between portfolio balance and technology transfer efficiency are studied. It is found that a balanced portfolio is correlated to technology transfer efficiency, which means Universities can structure its research portfolio to increase technology transfer efficiency.

Table of Contents

Dedicated to

My Family

Qiguo Zhang & Quanying Zhang

Tianqing Chen & Zhen Ye

Liying Zhang, Eric Zhang, Alan Zhang, Alex Zhang

Acknowledgements

It has been a great privilege to spend almost six years at Harvard. The best and worst moments of my doctoral journey have been shared with many people, who will always remain dear to me. I'd like to take this opportunity to thank them. It is their guidance, help and encouragement that made my PhD journey possible.

I am blessed to have Prof Eric Mazur as my dissertation advisor and mentor, whose guidance, support, and encouragement from the initial to the final stage of my PhD had made my Harvard experience a truly special and enjoyable one. I still remember his phone interview from Harvard when I was in Zhejiang University. I spent my first year at Harvard exploring both scientific research and technology ventures. I founded a technology start-up and raised angel investment in 2008. However, the fall of 2009 was my difficult times. Our company was almost running out of funding and we were losing employees. It was hard for me to continue my PhD and I doubted if PhD was really for me. Sleepless for almost three days, I turned to Prof Mazur. I would never forget the conversation I had with him in McKay café. He encouraged me to stay to complete my PhD. His words inspired me and gave me a sudden glimpse of hope in the dark mist of bewilderment. I realized that I'm actually interested in understanding how innovations are transferred to the industry and commercialized. It was the birth of my dissertation topic. Fortunately, our company was acquired in early 2010 with a decent valuation. I wouldn't be able to complete my PhD if I hadn't had that conversation with Prof Mazur. His endless guidance, support, and mentorship enabled me to develop fully as a PhD and as a person.

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I owe my deepest gratitude to my lost Prof Jin Au Kong. He was both professors at MIT and Zhejiang University. He was my advisor at Zhejiang University from Feb 2005 to June 2007. His integrity, passion, humor, and wisdom always inspired me. I vividly recollect every piece of insight that came from him. In his lecture, humorous stories and the anecdotes of Maxwell and other scientists interweave with electromagnetics in a natural way. I have learned not only Maxwell equations from him, but also many other aspects of life. I left Zhejiang University in July 2007 to pursue my PhD at Harvard. I didn't expect that I would never see him again. In the fall of 2007, I was busy with my first semester at Harvard and didn't get a chance to visit him in MIT until February 2008. But I was told he was sick in hospital then. One month later he passed away unexpectedly. Tears in my eyes, I blamed myself and endless regret on why I didn't visit him earlier. I hope the completion of my PhD could make him smile in heaven.

Last but not least, I thank my family and in-laws, who has provided me with unconditional love and support over the years and to whom I dedicate this work. Their love was my driving force. I owe them everything and wish I could show them just how much I love and appreciate them. I was fortunate to meet my wife the second day I arrived in Harvard. We have had three adorable kids. My wife's love and support allowed me to finish this journey. She already has my heart so I will just give her a heartfelt "thanks".

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List of Figures and Tables

List of Abbreviations

AUTM, Association of University Technology Managers;

Constant Returns to Scale, CRS;

DEA, Data Envelopment Analysis;

Decreasing Return to Scale, DRS;

DMU, Decision Making Unit;

EXPLGF, Legal Fee Expenditure;

FEDEXP, Federal Funding;

Increasing Return to Scale, IRS;

INVDIS, Invention Disclosure;

LCEXEC, Licenses Executed;

LICFTE, Number of Full-time Employees in Technology Licensing Office;

LIRECD, Licenses Income Received;

MI, Malmquist Index;

MPT, Modern Portfolio Theory;

SFA, Stochastic Frontier Analysis;

STRTUP, Number of Start-ups Initiated;

TTO, Technology Transfer Office; and

USPTIS, Number of US Patents Awarded.

Chapter 1 Introduction

1.1 University Technology Transfer

In general, technology transfer may be defined as the transfer of the research results from research institutions to the public (Bremer 1998). It may also be narrowly defined as the process of transferring the results of academic research from research institutions to other organizations in ways of licensing for the purpose of further development and commercialization (Carlsson and Fridh 2002) (Bauer and Flagg 2010). Technology transfer can occur in many different forms, including the publication of research results in scientific journals, dissemination of knowledge and research results in conferences and seminars to the public, and licensing technology to firms. In this dissertation, we are only studying the narrowly defined concept of technology transfer, i.e. the transfer from research institutions to the industry for commercialization.

1.2 The Bayh-Dole Act

It has been 33 years since the introduction of the Bayh-Dole Act of 1980, which gave universities the authority to commercialize discoveries made using federal funds (J. G. Thursby and Thursby 2003). The Bayh–Dole Act is United States legislation dealing with intellectual property arising from federal government-funded research. The Act was adopted in 1980. The Bayh-Dole Act changed the ownership of inventions made with federal funding from the federal government to universities, small businesses, or non-profit institutions (Stevens 2004).

In 1970s, the U.S. economy was plagued by the combination of soaring prices, the high unemployment, and low economic growth. The Congress took efforts to respond to the economy. One of Congress' efforts was on how to commercialize the inventions created from government sponsored research which has an annual funding of over $75 billion. These patents had accumulated because the government under President Roosevelt decided to continue and even ramp up its spending on research and development after World War II. It's based on Vannevar Bush's famous report "Science The Endless Frontier", which stated: "Scientific progress is one essential key to our security as a nation, to our better health, to more jobs, to a higher standard of living, and to our cultural progress."(Bush 1945). However, the government did not have a unified patent policy governing all the agencies that funded research. The general policy was that government would retain title to inventions and would license them only nonexclusively. (Bayh–Dole Act Wikipedia 2013) "Those seeking to use government-owned technology found a maze of rules and regulations set out by the agencies in question because there was no uniform federal policy on patents for government-sponsored inventions or on the transfer of technology from the government to the private sector." (United States General Accounting Office 1998).

Then Federal agencies started to use "Institutional Patent Agreements" to allow grantee companies or institutions to retain rights to inventions made with federal funding, but such agreements were not regularly used (Stevens 2004). In the 1970s, faculty at Purdue University in Indiana had made important discoveries under grants from the Department of Energy, which did not issue Institutional Patent Agreements (Stevens 2004). Officials at the university complained to their Senator, Birch Bayh. At the same time, Senator Robert Dole was thinking about similar issues, and the two senators collaborated on a bill later known as the Bayh-Dole Act (Stevens

2004). The legislation decentralized control of federally-funded inventions, vesting the responsibility and authority to commercialize inventions with the institution or company receiving a grant, with certain responsibilities to the government, the inventor, and the public, such as granting a royalty-free non-exclusive license to U.S. government for its own use (Bayh–Dole Act Wikipedia 2013).

Prior to the enactment of Bayh-Dole, the U.S. government had accumulated 28,000 patents but fewer than 5% of those patents were commercially license (United States General Accounting Office 1998). Shortly after the Bayh-Dole Act, there was a sharp increase in U.S. university patenting and licensing activity. There were 177 patents awarded to U.S. Academic Institutions in 1974 and 196 awarded in 1979 while There were 408 awarded in 1984, 1004 awarded in 1989, and 4700 awarded in 2011 (Mowery et al. 1999). In tandem with increased patenting, U.S. universities expanded their efforts to license these patents. The Association of University Technology Managers (AUTM) reported that the number of universities with technology licensing and transfer offices increased from 25 in 1980 to 200 in 1990, and licensing revenues of the AUTM universities increased from $183 million in 1991 to $3.44 billion in 2008. Moreover, the share of all U.S. patents accounted for by universities grew from less than 1% in 1975 to almost 2.5% in 1990 (Henderson, Jaffe, and Trajtenberg 1994). According to the AUTM 2010 Better World Report, in 30 years of Bayh-Dole Act, more than 6,000 new U.S. companies were formed from university inventions; 4,350 new university licensed products are in the market; 5,000 active university-industry licenses are in effect; more than 153 new drugs, vaccines or in vitro devices have been commercialized from federally funded research since enactment of Bayh-Dole. Between 1996 and 2007, university patent licensing made a $187 billion impact on the U.S. gross domestic product and a $457 billion impact on U.S. gross industrial output; and created 279,000 new jobs in the United States (Association of University Technology Managers 2010).

Bayh-Dole Act has been helping universities generate revenue by commercializing technology. The revenue is then re-invested in academic research (Grimaldi et al. 2011). This looks like a perfect cycle. However, there has been some concerns, such as publication delays and material transfer (Blumenthal et al. 1997; Louis et al. 2001; Mowery 2004; Perkmann and Walsh 2008), a deterioration of the open culture of academic research, and that universities are performing less basic research and are becoming capitalized (Welsh et al. 2008; J. Thursby and Thursby 2010).

1.3 The technology transfer process

The process starts with the inventor submitting an invention disclosure form to the University Technology Transfer Office (TTO). After reviewing the disclosure, investigating the potential market, and estimating whether or not the expected return exceeds the cost of seeking intellectual property protection (patent, copyright, trademark, or other form of protection), the TTO initiates the requisite application. The patenting cost about $20,000. Once intellectual property rights have been obtained, technology licenses are typically developed in several stages as shown in the following figure.

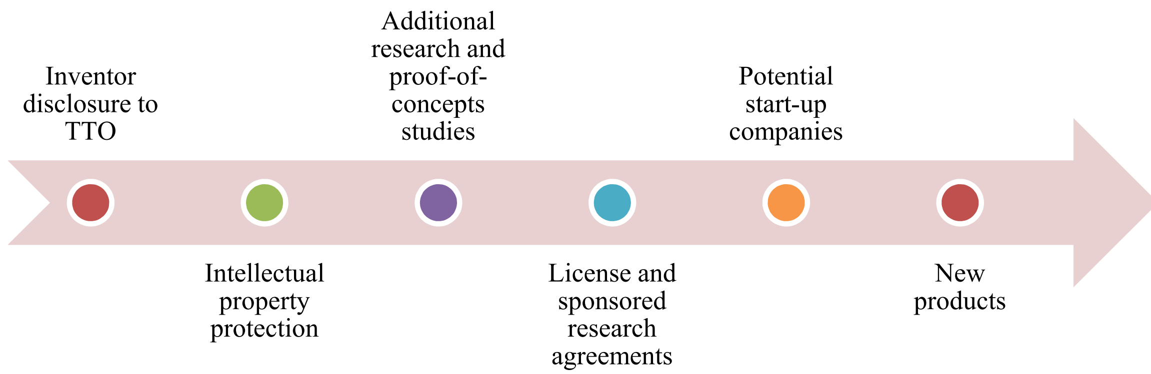


Figure 1.1: Road map for typical U.S. patent prosecution (Harvard University Office of Technology Development 2009).

1.4 Organization of This Study

In this dissertation, I first analyzed the 1998-2011 survey data from The Association of University Technology Managers (AUTM) in Chapter 2. I studied University research fund composition, technology transfer office staffing, licenses executed to start-ups, small companies, and large companies, license income composition, legal fee expenditures, new patents applications, provisional patents, utility patents, and non USA patents, invention disclosures, U.S. patents issued, start-ups initiated, and annual averages of U.S. University technology transfer offices.

In Chapter 3 first outlines the theoretical background of Data Envelopment Analysis that is used to assess the efficiencies of university technology transfer. A two-stage model is proposed and efficiencies of the 100 Universities in our sample pool are assessed for both stages. Then Malmquist Index is used to measure year to year productivity change. In the end, the correlation between technology transfer and academic reputation is studied.

Chapter 4 applied Modern Portfolio Theory to University research portfolio management. University disciplines are categorized into three major disciplines: engineering, physical and mathematical sciences, and biological and life sciences. The risk and return of technology transfer are defined and research portfolio risk-return curve are solved. Then correlation between portfolio balance and technology transfer efficiency are studied.

Chapter 5 goes into a summarization of the findings, contributions, managerial implications, and also proposes areas for future research.

Chapter 2 University Technology Transfer Activity Analysis

The analysis in this Chapter is based on the data from the annual survey conducted by The Association of University Technology Managers (AUTM). The analysis gives us an overall understanding of the industry. AUTM is an organization devoted to promoting technology transfer between universities and the industry. The association was founded in 1974 and now has over 3,500 members worldwide.

2.1 University Research Funds

University research funds come from three major sources: Federal Funding, Industrial Funding, and other sources. Figure 2.1 shows U.S. Universities research funding of all the respondents from AUTM survey. Total research funding reached a historical high of $61.4 Billion in 2011 with a Compound Annual Growth Rate (CAGR) of 7.72% from 1998 to 2011. Federal funding is the major source for University research and accounts for about 65.5% in 2011 with a CAGR of 7.99% from 1998-2011. It enjoyed a 17.5% increase from 2009 to 2010 due to the economic stimulus package. Industrial funding accounts for 6.6% of total funding in 2011. It has a CAGR of 4.8% from 1998 to 2011, which is lower than both Federal funding and other sources.

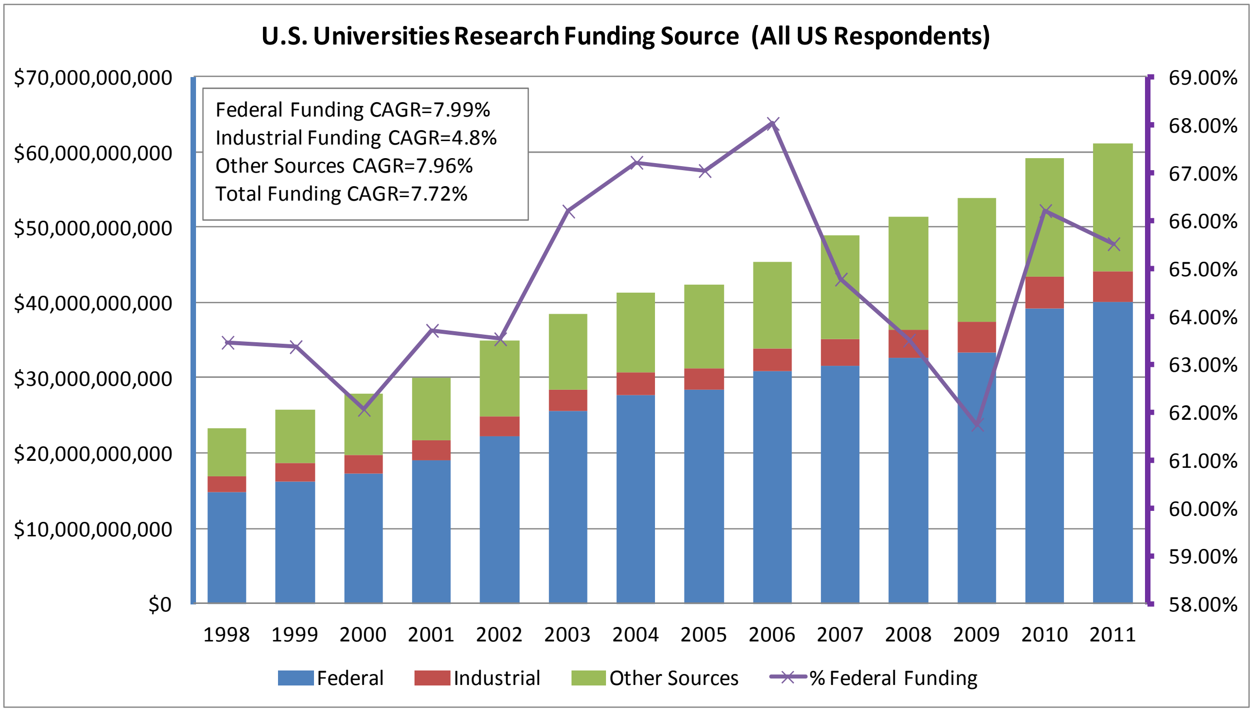


Figure 2.1: U.S. Universities research funding source (data source: Association of University Technology Managers Licensing Surveys).

2.2 Technology Transfer Office Staffing

There are two types of staff in a typical University Technology Transfer Office: the licensing employees and supporting employees. We use the number of licensing employees to measure the size of a Technology Transfer office. The total number enjoyed a steady growth with a CAGR of 6.56% from 1998 to 2009 as shown in the figure below. Even in during the Dot-com bubble, it didn't decline. From 2009 to 2011, the total number declined from 1050 to 1033. The average number of full-time licensing employees per University declined from 5.9 people in 2009 to 5.7 people in 2011. This is due to layoff during the financial crisis.

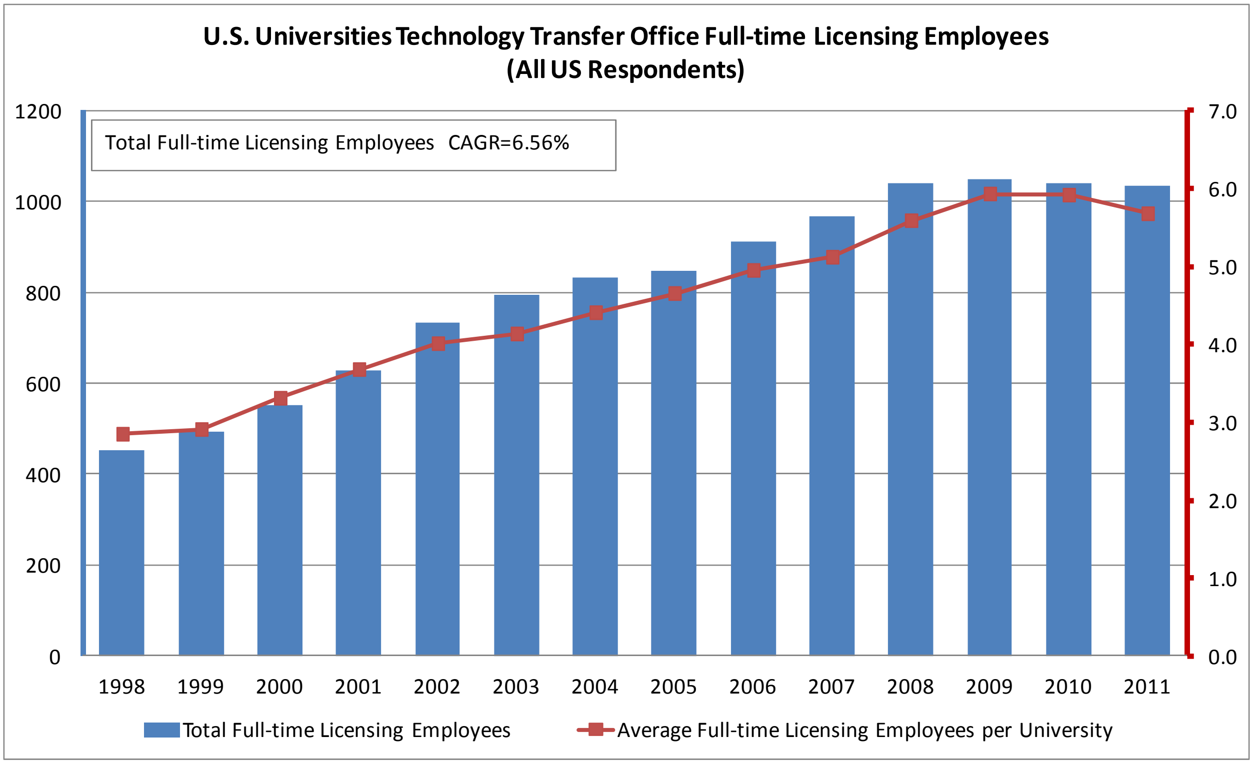


Figure 2.2: Universities technology transfer office full-time licensing employees (data source: Association of University Technology Managers Licensing Surveys).

2.3 Licenses Executed and License Income

Licenses can be executed to start-ups with a CAGR of 6.69%, small companies with a CAGR of 4.58%, and large companies with a CAGR of 3.27%. Percentage of licenses executed to start-ups increased from 11% in 1998 to 15% in 2011, indicating a preference favoring start-ups. Licenses executed to small companies accounts for about half of executed licenses. The percentage remains fairly constant over the years. Percentage of licenses executed to large companies declined from 36.5% in 1998 to 31.5% in 2011.

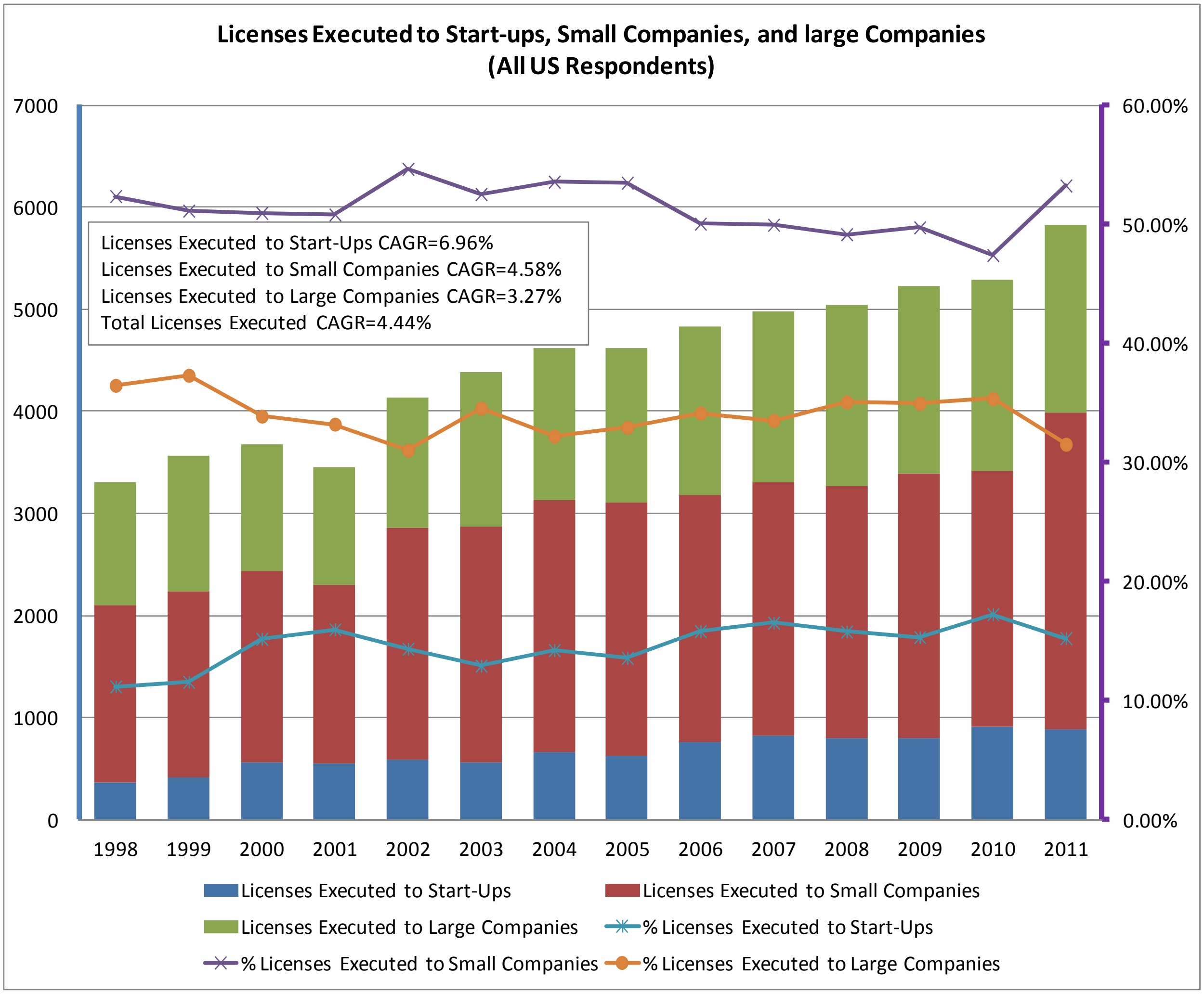


Figure 2.3: Licenses executed to start-ups, small companies, and large companies (data source: Association of University Technology Managers Licensing Surveys).

Total license income enjoyed a steady growth from 1998 to 2008 with the exception of 2001 because of the Dot-com bubble. It dropped by 30% in 2009 and then grew slowly till 2011 as shown in the figure below. The significant drop is caused by the financial crisis. So it is observed that total income is significantly correlated with the economy. The overall CAGR is 8.21% from 1998 to 2011. Running royalties has a CAGR of 8.21% and accounts for about 60% of total income in 2011. The increase in running royalties is an indication that university discoveries are making their way to the economy. Cashed-in equity has a CAGR of 3.36% and accounts for only 2.6% of total income in 2011. All other sources of income (e.g., license issue fees, payments under options, termination payments, and annual minimums) have a CAGR of 11.91%. Not characterized income is the difference between total income received minus running royalties, cashed-in equity, and other sources of income. It needs to be studied further because it grew rapidly with a CAGR of 10.8% in the past 13 years and now accounts for 20% of the total income in 2011.

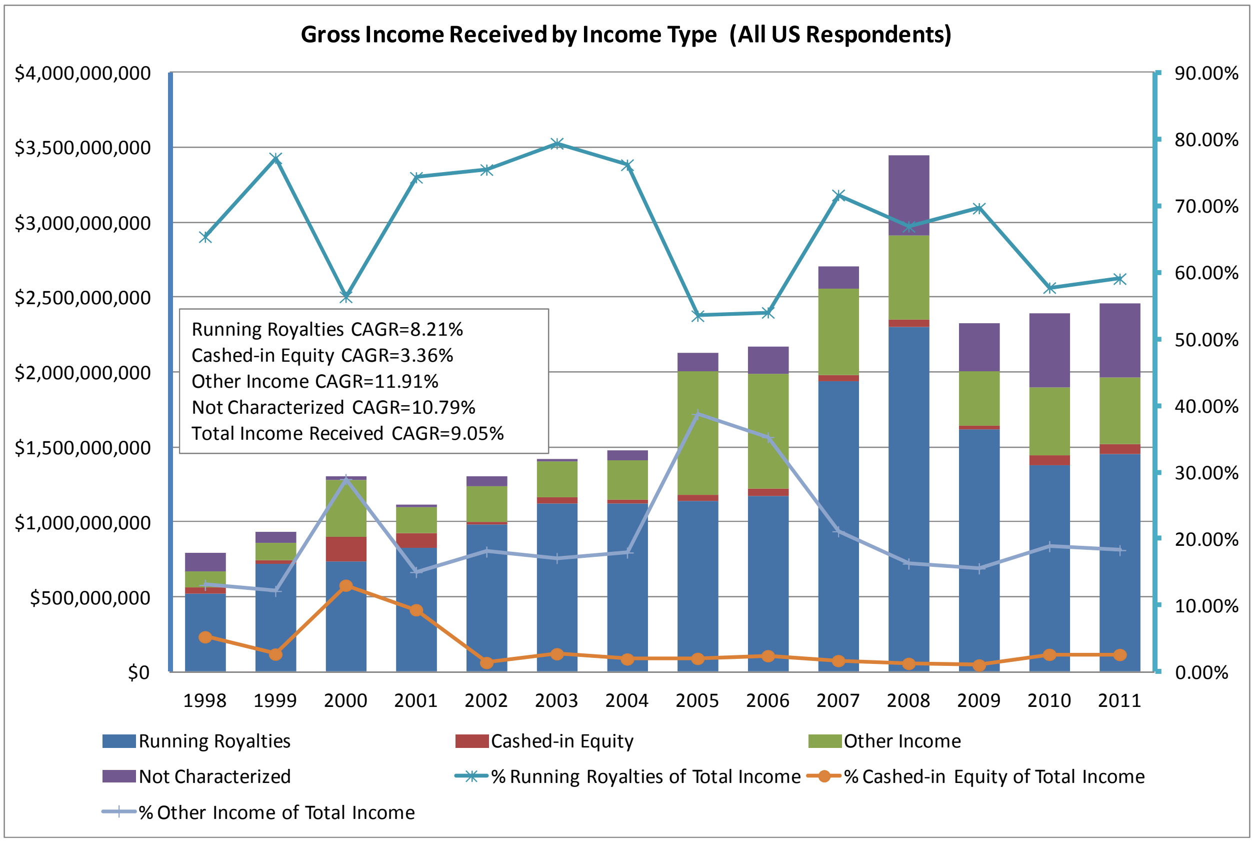


Figure 2.4: Gross income received by income type (data source: Association of University Technology Managers Licensing Surveys).

The above data is of about the technology transfer industry as a whole. If we look into a single license or University, we will find that license income distribution is highly skewed (Scherer and Harhoff 2000). Most innovations yield modest returns, but a few innovations have particularly high returns. One blockbuster patent can result in a lot of money. For example, the synthesis of Taxol patent of Florida State University (FSU) was approved by the US Food and Drug

Administration (FDA) for the treatment of ovarian, breast, lung, and testicular cancer. In 2000-2001, the royalty paid to FSU by Bristol-Myers Squibb was about $67 million. Table 2.1 shows the distribution of full-term U.S. patent values (Harhoff, Scherer, and Vopel 2003). The 225 patents in the table have a 1977 priority date, leading to patents expiring at full term during 1995. It is observed that less than 10% of the patents generated more than 70% of the total value.

Table 2.1: Distribution of full-term U.S. patent values (Harhoff, Scherer, and Vopel 2003).

Estimated Value Range	Number	Number Percent	Value Percent
More than $100 million	22	9.8	70.42
$50-100 million	6	2.7	9.60
$20-50 million	10	4.4	7.47
$5-20 million	34	15.1	9.07
$1-5 million	41	18.2	2.62
$500,000 to $1 million	30	13.3	0.48
$100,000 to $499,999	45	20	0.29
Less than $100,000	37	16.4	0.04
Total	225	100	100

2.4 Legal Fee Expenditures and Legal Fees Reimbursed

Legal fees expenditures include the amount spent by a University in external legal fees for intellectual property protection. Legal fees reimbursements is paid via lump sum payments of costs incurred in prior years when a new license is signed and regular reimbursements of new costs incurred after the license is signed. The percentage of legal fees out of total licensing income remains pretty constant around 13% in the past 13 years.

The percentage of legal fees reimbursement increased from 41% in 1998 to its peak of 49% in 2009. Then it declined a little bit to 47% in 2011, indicating Universities' reluctance to increase their resource commitment to technology transfer because of the financial crisis, which is also reflected in the declining technology transfer office employment from 2009 to 2011 as shown in Figure 2.5.

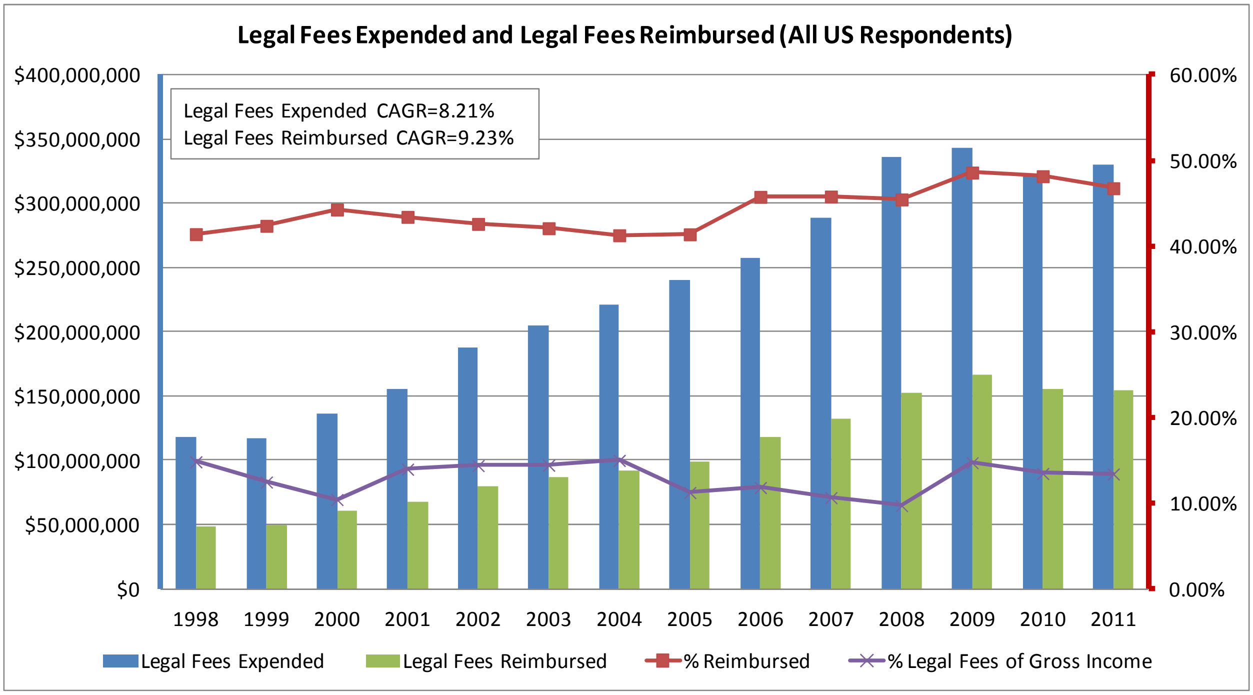


Figure 2.5: Legal fees expended and legal fees reimbursed (data source: Association of University Technology Managers Licensing Surveys).

2.5 New Patents Applications

In the United States, besides new patent applications to protect new inventions, there are several other types of patent applications to cover new improvements to their inventions or to cover different aspects of their inventions. These types of patent applications include continuation, divisional, continuation in part, and reissue. We compare the total patents filed with newly filed in Figure 2.6. Total filed has a CAGR of 7.98% while newly filed has a CAGR of 8.48%. The ratio has remained fairly stable around 65% from 1998 to 2011.

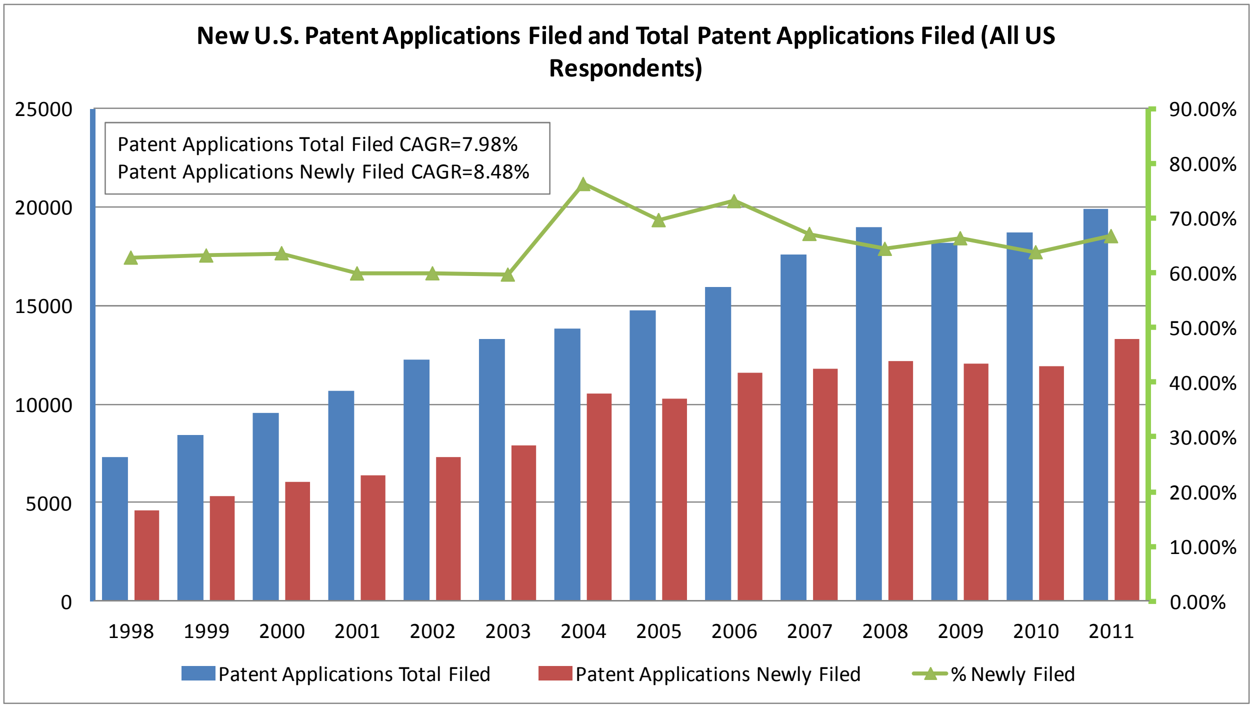


Figure 2.6: New U.S. patent applications filed and total patent application filed (data source: Association of University Technology Managers Licensing Surveys).

2.6 Provisional Patents, Utility Patents, and Non USA Patents

New patents application has an overall CAGR of 3.87% from 2004 to 2011. We break new patent applications into three categories: Provisional Patents with a CAGR of 6.34%, Utility Patents with a CAGR of -2.47%, and Non USA Patents with a CAGR of -0.96%.

New non-U.S. patent applications include any initial patent filing of an invention disclosure made outside of the U.S., including Patent Cooperation Treaty (PCT) applications, utility applications filed in patent offices other than the USPTO and provisional applications filed outside of the United States such as UK or New Zealand provisional applications and incomplete applications in Canada.

Provisional filings represent the most common form of new patent application. In 2011, Provisional patents accounts for 76.3% of total new patents applications, new Utility patent accounts for 9.6%, and Non USA patents accounts for 14.1%. There was an increase in almost every category of patent application. Provisional patent increased by 9% compared to 2010. It is probably too early to tell if this is a direct result of the America Invents Act.

The Leahy-Smith America Invents Act (AIA) is United States federal legislation that was passed by Congress and was signed into law by President Barack Obama on September 16, 2011. The law represents the most significant change to the U.S. patent system since 1952. The law switched U.S. rights to a patent from the present "first-to-invent" system to a "first inventor-to-file" system for patent applications filed on or after March 16, 2013. In part for this reason, the U.S. Patent and Trademark Office is likely to see increased numbers of provisional applications, which if done properly can be a cost-effective way to obtain an early priority date for a patent application.

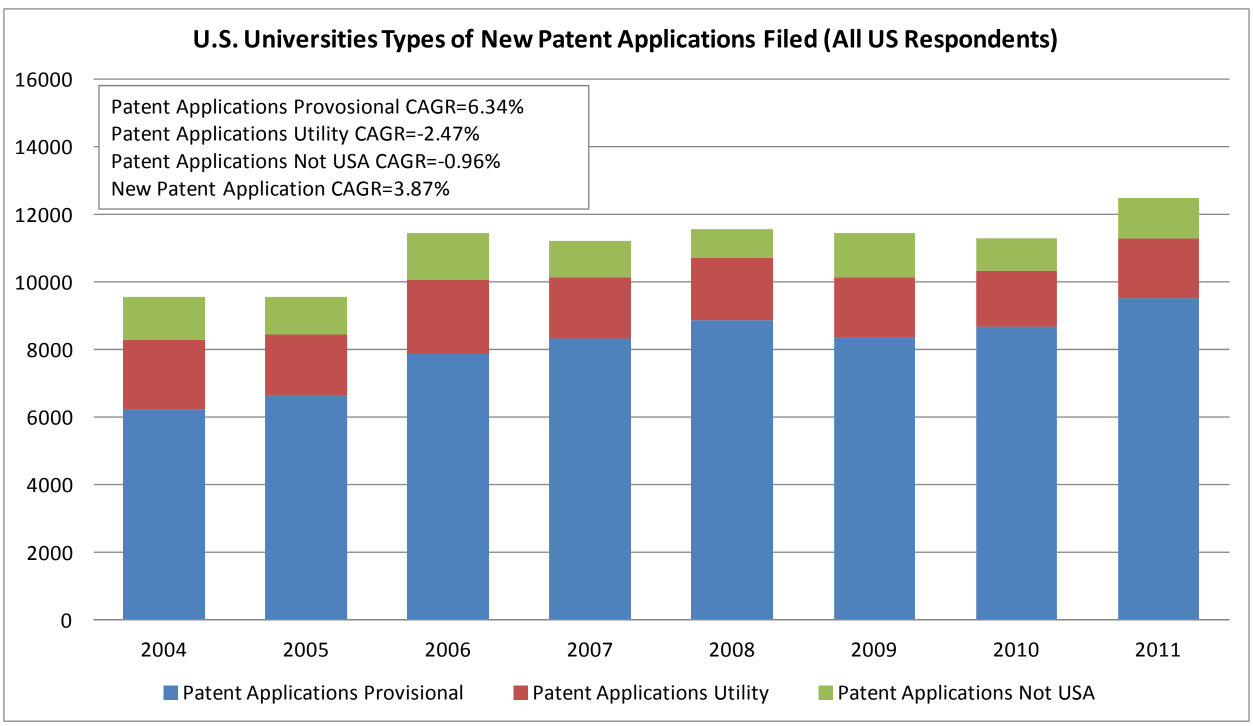


Figure 2.7: U.S. universities types of new patent applications filed (data source: Association of University Technology Managers Licensing Surveys).

2.7 Invention Disclosures, New Patents Application, and U.S. Patents Issued

Invention disclosure is a direct measurement of discoveries, which has a CAGR of 5.43% from 1998 to 2011. Patent Application Newly Filed has a CAGR of 8.48%, and U.S. Patents issued has a CAGR of 3.15% from 1998 to 2011. In Figure 2.8, it is observed that the percentage to pursue patents out of invention disclosure increased from 42% in 1998 to 61% in 2011, indicating Universities' tendency to pursue intellectual protection increased. However, the approval percentage of newly filed patents dropped from 68% to 35%, yielding a drop in U.S. patents issued out of invention disclosure from 29% in 1998 to 22% in 2011. We assume United States Patent and Trademark Office's patents reviewing system didn't change over the years, or in other words, didn't become stricter. Then the quality of inventions disclosures dropped in the past 13 years.

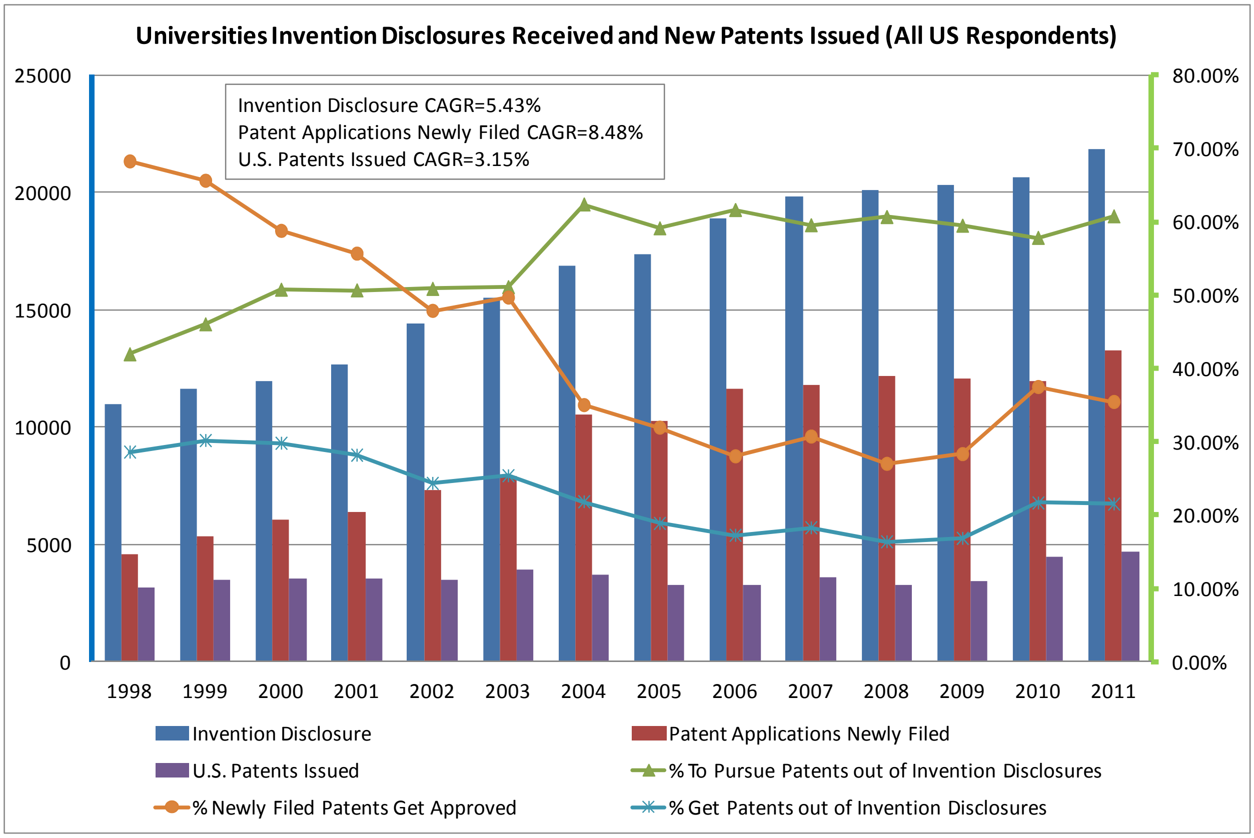


Figure 2.8: Universities invention disclosures received and new patents issued (data source: Association of University Technology Managers Licensing Surveys).

2.8 Start-ups Initiated

The number of start-ups initiated grows steadily with a CAGR of 6.23% from 2000 to 2011 as shown in the figure below. However, the CAGR of start-ups that Universities hold equity is 3.71%, which is lower than the CAGR of start-ups initiated. Although the number of start-ups that University hold equity grew, the percentage of start-ups that Universities hold equity declined over the past 11 years, indicating Universities' increased unwillingness to take equity as payment in licenses. This sounds contradictory to the licensing preference favoring start-ups mentioned in Section 2.3. However, it does not. Universities prefer to execute a license to start-ups but don't like to take equity.

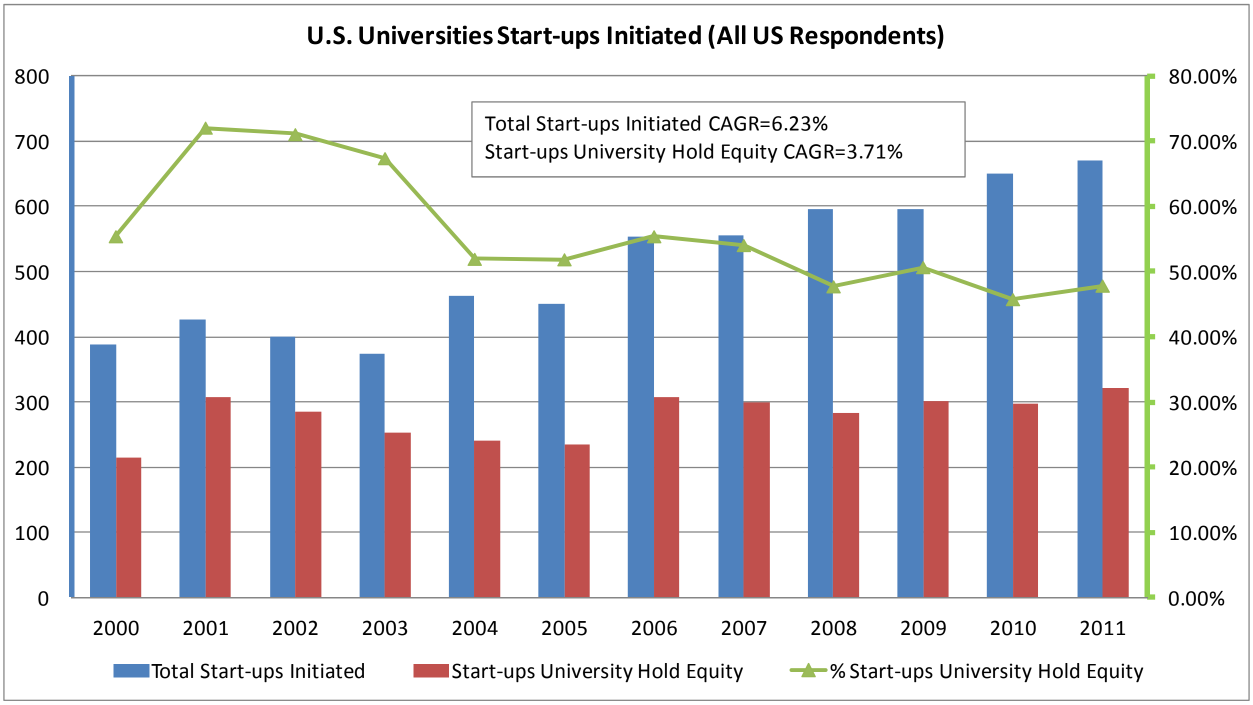


Figure 2.9: U.S. universities start-ups initiated and start-ups university hold equity (data source: Association of University Technology Managers Licensing Surveys).

2.9 Annual Average of U.S. University Technology Transfer Offices

Following is the annual averages of U.S. University technology transfer offices. It gives a palpable idea of an average University technology office in the United States.

Table 2.2 Annual averages of U.S. university technology transfer offices.

YEAR	NOPARU	LICFTE	TOTEXP	FEDEXP	INDEXP	OTSOUR	LCEXSU	LCEXSM	LCEXLG	LCEXEC	LIRECD	LIRUNR	CAINEQ	LIOTHR	NOCHAR	EXPLGF	REIMLG	INVDIS	TPTAPP	NPTAPP	USPTIS	STRTUP
1998	159	2.85	$146,219,007	$92,781,619	$13,751,768	$39,685,620	2.33	10.90	7.59	21.52	$5,010,925	$3,273,325	$264,619	$654,836	$818,145	$744,354	$308,304	69.10	46.16	28.96	19.75	1.92
1999	170	2.91	$151,038,385	$95,700,430	$14,447,570	$40,890,385	2.42	10.72	7.82	21.69	$5,505,234	$4,246,751	$147,830	$669,462	$441,191	$687,813	$291,589	68.28	49.75	31.41	20.59	1.73
2000	167	3.31	$166,903,269	$103,568,217	$14,715,592	$48,619,460	3.34	11.22	7.46	24.12	$7,792,419	$4,387,217	$1,014,793	$2,255,616	$134,793	$814,747	$360,827	71.70	57.23	36.37	21.36	2.32
2001	171	3.68	$175,214,287	$111,617,625	$14,702,955	$48,893,707	3.22	10.25	6.70	21.78	$6,501,008	$4,825,861	$607,149	$975,616	$92,382	$909,686	$395,046	73.89	62.50	37.41	20.81	2.49
2002	183	4.01	$191,076,310	$121,382,553	$14,833,581	$54,860,176	3.24	12.35	7.01	23.56	$7,127,277	$5,373,647	$101,334	$1,287,533	$364,763	$1,027,426	$437,872	78.68	66.79	39.99	19.13	2.19
2003	192	4.13	$200,654,706	$132,818,065	$14,887,852	$52,948,790	2.95	12.01	7.90	23.52	$7,389,877	$5,863,372	$202,136	$1,263,745	$60,623	$1,068,309	$449,841	80.78	69.17	41.26	20.48	1.95
2004	189	4.41	$218,225,230	$146,672,160	$15,546,645	$56,006,425	3.48	13.11	7.88	25.31	$7,798,714	$5,936,601	$152,483	$1,398,423	$311,206	$1,171,726	$483,873	89.26	73.03	55.65	19.47	2.44
2005	182	4.65	$232,450,541	$155,833,234	$16,091,691	$60,525,615	3.45	13.59	8.37	27.10	$11,701,162	$6,255,593	$238,526	$4,528,777	$678,266	$1,319,121	$546,172	95.51	81.08	56.43	18.01	2.48
2006	184	4.95	$246,556,411	$167,717,471	$16,078,843	$62,760,097	4.15	13.13	8.96	26.97	$11,808,847	$6,372,445	$288,905	$4,162,575	$984,922	$1,398,675	$640,219	102.58	86.46	63.16	17.69	3.01
2007	189	5.12	$258,426,678	$167,389,371	$18,374,053	$72,663,253	4.35	13.16	8.83	27.03	$14,321,914	$10,251,707	$244,761	$3,024,771	$800,675	$1,529,250	$700,454	104.90	93.06	62.42	19.16	2.94
2008	186	5.59	$276,696,405	$175,696,290	$20,057,607	$80,942,509	4.27	13.32	9.50	27.59	$18,515,914	$12,381,332	$238,625	$3,014,901	$2,881,056	$1,804,677	$820,657	108.15	101.88	65.56	17.69	3.20
2009	177	5.93	$304,793,680	$188,183,368	$22,796,605	$93,813,707	4.52	14.67	10.31	30.10	$13,140,385	$9,145,922	$137,832	$2,044,244	$1,812,387	$1,938,226	$942,236	114.74	102.89	68.20	19.31	3.37
2010	176	5.92	$336,022,171	$222,455,588	$24,268,044	$89,298,539	5.18	14.25	10.63	30.47	$13,610,928	$7,851,853	$360,139	$2,569,704	$2,829,232	$1,836,442	$884,624	117.28	106.35	67.78	25.39	3.70
2011	182	5.68	$336,027,993	$220,138,932	$22,088,359	$93,800,701	4.87	17.03	10.08	33.21	$13,506,744	$7,972,710	$355,152	$2,470,370	$2,708,512	$1,814,385	$848,821	120.09	109.37	72.92	25.82	3.69
CAGR	1.04%	5.45%	6.61%	6.87%	3.71%	6.84%	5.85%	3.49%	2.21%	3.39%	7.93%	7.09%	2.29%	10.75%	9.65%	7.09%	8.10%	4.34%	6.86%	7.36%	2.08%	5.13%

Note:

NOPARU	Number of Participating Universities	LIRUNR	Running Royalties
LICFTE	Full-time Licensing Employees	CAINEQ	Cashed-in Equity
TOTEXP	Research Expenditures	LIOTHR	Other Income
FEDEXP	Federal Funding	NOCHAR	Not Charaterized
INDEXP	Industrial Funding	EXPLGF	Legal Fees Expended
OTSOUR	Other Sources	REIMLG	Legal Fees Reimbursed
LCEXSU	Licenses Executed to Start-Ups	INVDIS	Invention Disclosure
LCEXSM	Licenses Executed to Small Companies	TPTAPP	Patent Applications Total Filed
LCEXLG	Licenses Executed to Large Companies	NPTAPP	Patent Applications Newly Filed
LCEXEC	Total Licenses Executed	USPTIS	U.S. Patents Issued
LIRECD	License Income Received	STRTUP	Average Start-ups Initiated per University
CAGR	Compound Annual Growth Rate		

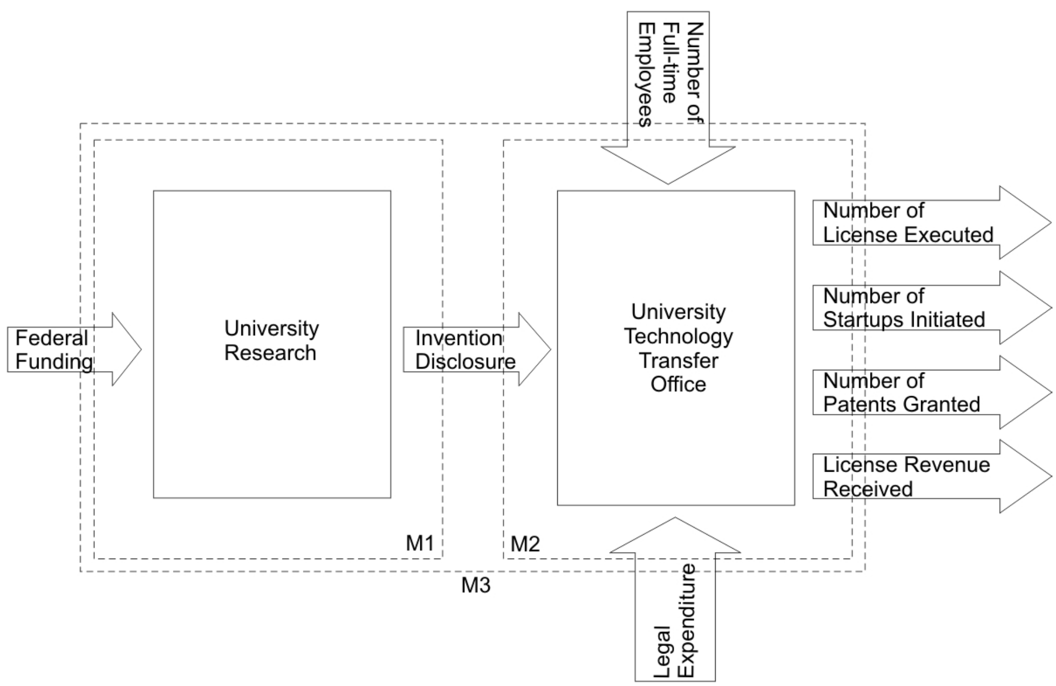
Chapter 3 Assessing University Technology Transfer Efficiency

3.1 A Two-stage Model of Technology Transfer

Siegel and et al (Siegel, Waldman, and Link 2003) used Stochastic Frontier Analysis (SFA) (Battese and Coelli 1995) to assess the impact of organizational practices on the relative productivity of university technology transfer offices (TTO). However, SFA can only handle one output, or a priori weighted average of multiple outputs. SFA allows for statistical inference, but requires restrictive functional form and distribution assumptions.

Thursby and Kemp (J. G. Thursby and Kemp 2002) used Data Envelopment Analysis (DEA) (Cooper, Seiford, and Zhu 2011) (Charnes, Cooper, and Rhodes 1978) to assess the growth and productive efficiency of university intellectual property licensing. However, only 1991-1996 data from the Association of University Technology Managers (AUTM) licensing survey was available. As we know, AUTM starts its licensing survey in 1991 and there are not many participating universities until 1995. In addition, the model Thursby and Kemp (J. G. Thursby and Kemp 2002) used is a single stage model. It doesn’t evaluate the efficiencies of university research and technology transfer office separately.

The above research didn’t address the question whether inefficiency is from university research or from the technology transfer office. Therefore, we propose a two-stage model, the university research module and university technology transfer module. We will assess their efficiencies separately and then as a whole. Some universities focus more on basic research which produce less patents and commercially rewarding inventions. If we model the university research and technology transfer office as a whole, then it is inefficient. However, if we model it in a two-stage model, we can find that the same amount of federal funding produce less invention disclosure because of the basic research tendency. Its overall efficiency is low is not caused by TTO inefficiency but by its basic research tendency and hence less invention disclosures. If we don’t use a two-stage model, we will undervalue its TTO efficiency. By modeling university technology transfer in a two-stage model, it offers better insights for university technology transfer management.



The dashed rectangle M1 is the research part of a university, which has one input: federal funding and one output: invention disclosure. The dashed rectangle M2 is the technology transfer office of a university, which has three inputs: number of full-time employees, legal expenditure, and invention disclosure and four outputs: number of license executed, number of startups initiated, number of patents granted, and license revenue received. The dashed rectangle M3 denotes university as a whole which include both the research part and technology transfer office. It has three inputs: federal funding, number of full-time employees, and legal expenditure and four outputs: number of license executed, number of startups initiated, number of patents granted, and license revenue received.

Figure 3.1: Two-stage model of university technology transfer.

3.2 Technical Efficiency, Allocative Efficiency, and Economic Efficiency

Before assessing university technology transfer efficiency, we have to distinguish three different efficiencies: technical efficiency, allocative efficiency, and economic efficiency (Bhagavath 2006). The most common efficiency concept is technical efficiency. A producing unit is "technically inefficient" if it is possible to produce more output with the current level of inputs or, equivalently, it is possible to produce the same output with fewer inputs. In other words, given current technology, there is no wastage of inputs in producing the given quantity of output. An organization is 100% technically efficient if it operates at best practice. If it operates below best practice, then the organization's technical efficiency is expressed as a percentage of best practice. Managerial practices and the scale of operations affect technical efficiency.

Technical efficiency doesn't factor in the prices of input. Assuming an organization is already 100% technical efficient, which means there are no way we could produce more output for a given level of input. However, it doesn't mean we cannot allocate inputs proportions differently, given relative input prices, to minimize the input cost without sacrificing the level of output. This is the concept of allocative efficiency. It is also expressed as a percentage score, with a score of 100% indicating that the organization is using its inputs in the proportions that would minimize costs.

Finally, economic efficiency refers to the combination of technical and allocative efficiency. Economic efficiency is calculated as the product of the technical and allocative efficiency scores, so an organization can only be 100% economic efficient if it is both 100% technical efficient and allocative efficient.

These concepts are best depicted graphically in Figure 3.2 (Farrell 1957). There are two-input (labor and capital) and one output. The isoquant curve (efficient frontier) is a smooth contour line representing theoretical best engineering practice. All the points on the isoquant curve have the same quantity of output with the minimum amounts of the two inputs required to produce that amount of output. Producers can change input combinations along the isoquant curve without changing the output quantity. Any organization operating on the isoquant curve is technically efficient.

The budget line draw through a set of points that have the same total input cost. The slope of the budget line is the negative ratio of the capital price to the labor price. Budget lines closer to the origin represent a lower total cost. Therefore, the cost of producing a given output quantity is minimized at the point where the budget line is tangent to the isoquant, i.e. point C in the figure. Both technical and allocative efficiencies are achieved at point C. Point B is also technically efficient but its input combination cost more because it's on a budget line further away from the origin than point C.

Suppose an organization is operating at point A, producing the same output as point A' then A would be technically inefficient because more inputs are used than are needed to produce the given amount of output. So its technical efficiency can be calculated as $\frac{OA'}{OA}$. Its allocative efficiency can be calculated as $\frac{OA''}{OA'}$.

$$Economic\ Efficiency = (Technical\ Efficiency) * (Allocative\ Efficiency)$$
$$EE = TE * AE$$
$$\frac{OA''}{OA} = \frac{OA'}{OA} * \frac{OA''}{OA'}$$

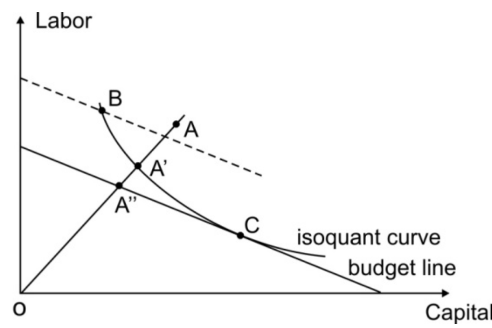


Figure 3.2: Technical efficiency, allocative efficiency, and Economic Efficiency.

The technology transfer efficiency we study in this research is technical efficiency because cost of inputs is not included.

3.3 Data Envelopment Analysis

Data Envelopment Analysis (DEA) is developed by Charnes et al. (Charnes, Cooper, and Rhodes 1978) and further developed by Banker et al. (Banker, Charnes, and Cooper 1984). It is a non-parametric method used for the measurement of efficiency in cases where multiple input and output factors are observed and when it is not possible to turn these into one aggregate input or output factor. Unlike parametric methods, DEA makes no assumptions about the form of the production function and doesn't specify a predefined function to measure its efficiency. The actual inputs and outputs observed are used to estimate a benchmark production frontier. DEA measures the comparative efficiency of the units to be evaluated. These units are called Decision Making Units (DMU). The relative efficiency of a DMU is defined as the ratio of the total weighted output to the total weighted input (Ray 2004).

3.3.1 Efficiency Frontier

Given the strengths of DEA, we use it to find the efficiency frontier and assess university technology transfer efficiency. The basic idea of how to use DEA to find the efficiency frontier and assess efficiency can be illustrated graphically with the simple single input two-output example below (Anderson 2013). Suppose there are three Farms A, B, and C with the same number of workers but different outputs as shown in Table 3.1.

Table 3.1 Input and output of three farms A, B, and C.

	Input	Output	Output
Farm A	10 workers	40 apples	0 oranges
Farm B	10 workers	20 apples	5 oranges
Farm C	10 workers	10 apples	20 oranges

Figure 3.3 shows the three farms graphically**.** It is assumed that convex combinations of farms are allowed, then the line segment connecting farms A and C shows the possibilities of virtual outputs that can be formed from these two farms. Similar segments can be drawn between A and B along with B and C. Since the segment AC lies beyond the segments AB and BC, this means that a convex combination of A and C will create the most outputs for a given set of inputs. Please note C is connected to the vertical axis using a horizontal line. It's because a farm can always produce less apples with the same amount of input as C. But we have no knowledge of whether producing less apples would allow it to raise its oranges production so we have to assume that it remains constant. Therefore, the blue line is called the efficiency frontier, which

defines the maximum combinations of outputs that can be produced for a given set of inputs. Farm B lies below the efficiency frontier, which means it is inefficient. Its efficiency can be determined by comparing it to a virtual farm formed from a combination of farm A and C. The virtual farm, called V, is approximately 64% of farm C and 36% of farm A. (This can be determined by the lengths of AV, CV, and AC. specifically, Farm V=(Farm C)*(CV/AC) + (Farm A)*(AV/AC).

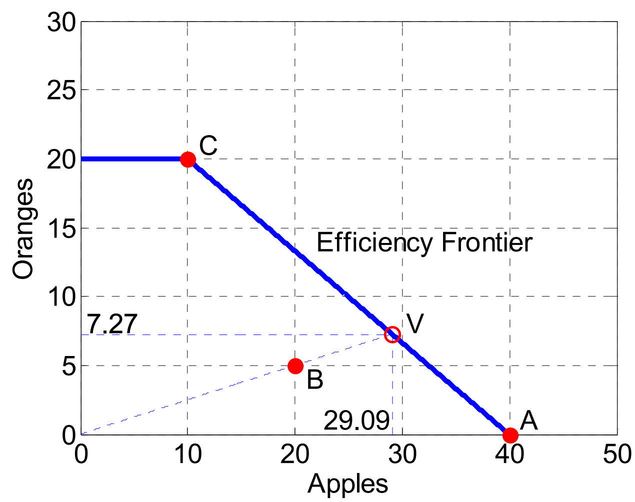


Figure 3.3: Efficiency frontier of three Farms A, B, and C.

The efficiency of farm B is calculated by finding the fraction of inputs that farm V would need to produce as many outputs as farm B. This is easily calculated by looking at the line OV. The efficiency of farm B is OB/OV which is approximately 68%. This figure also shows that farms A and C are efficient since they lie on the efficiency frontier. Therefore the efficiency of farms A and C are 100%.

The graphical method is useful in this simple example but gets much harder in higher dimensions. We will then use Linear Program formulation of DEA.

3.3.2 Returns to Scale

Since this problem uses a constant input value of 10 for all of the farms, it doesn’t have the complications of different returns to scale. Returns to scale refers to increasing or decreasing efficiency based on size. Constant Returns to Scale (CRS) means that output linearly increase or decrease with the increase or decrease of input without increasing or decreasing efficiency. Increasing Return to Scale (IRS) means a producer can achieve certain economies of scale by producing more. Decreasing Return to Scale (DRS) means a producer find it more and more difficult to keep the output proportionally with the increase of input. Variable returns to scale (VRS) is having both IRS and DRS in certain ranges of production. The assumption of CRS may be valid over limited ranges but its use must be justified. In general, CRS tends to lower the efficiency scores while VRS tends to raise efficiency scores.

In the following figure, it shows different returns to scale by moving a producer from operation point A’ to A’’. In Figure 3.4 (a). CA’/CA=BA/BA’’, so it is constant return to scale. In Figure 3.4 (b), CA’/CA<BA/BA’’, so it is decreasing return to scale. In Figure 3.4 (c), CA’/CA>BA/BA’’, so it is increasing return to scale.

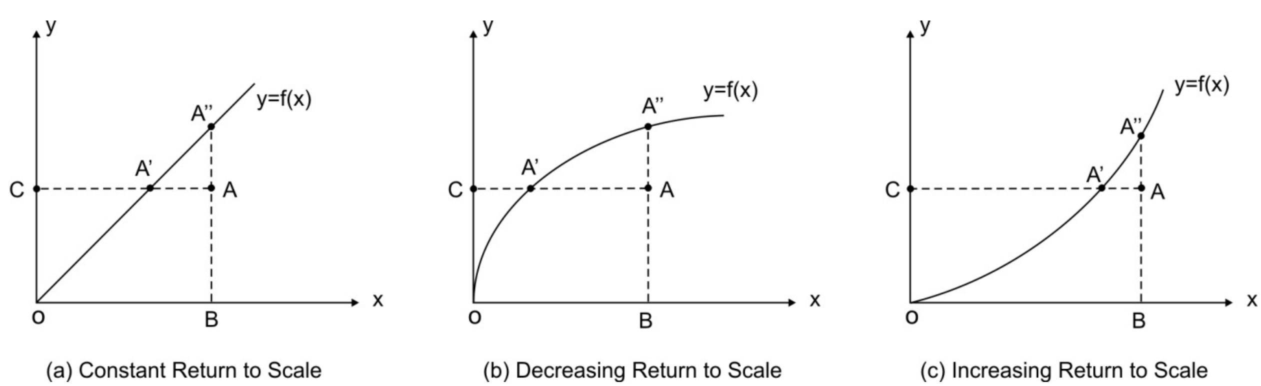


Figure 3.4: Return to scale.

In Figure 3.4 (b), we have decreasing returns to scale represented by y=f(x), and an inefficient firm operating at the point A. The input-orientated measure of Technical Efficiency would be

CA'/CA because it measures how much the input can be proportionally reduced without changing the output. On the other hand, the output-orientated measure of Technical Efficiency would be BA/BA'' because it measures how much the output can be proportionally increased without changing the input. When constant return to scale, the input and output oriented Technical Efficiency would be the same, but will be unequal when increasing or decreasing returns to scale are present (Fare and Lovell 1978). The constant returns to scale case is depicted in Figure 3.4 (a) where CA'/CA= BA/BA''. It is easy to observe from the curves that in the case of DRS, input oriented Technical Efficiency is tend to be smaller than output oriented Technical Efficiency while in the case of IRS, input oriented Technical Efficiency is tend to be larger than output oriented Technical Efficiency.

3.3.3 Input-Oriented and Output-Orientated Measures

The difference between the output- and input-orientated measures can further in a two-input and single output case as shown in Figure 3.5 (a). Assume an inefficient organization is operating at point A with the same output as point A'. It is easily observed that we can reduce its input by OA'/OA without decrease the output, so its technical efficiency TE= OA'/OA. If we have input price information then we can draw the iso-cost line A''C. It is seen from the figure that we can reduce the total input cost by OA''/OA' if we move from point A' to point C without decreasing output. So its allocative efficiency AE= OA''/OA'. Therefore its economic efficiency EE = TE*AE = (OA'/OA) * (OA''/OA') = OA''/OA.

Similarly, we can consider the output-oriented measure further by considering a single input and two-output case as shown in Figure 3.5 (b). Assume an inefficient organization is operating at point A with the same output as point A'. Please note, inefficient operation point lies outside of the iso-output curve in the case of input-oriented while it lies inside of the iso-input curve.

It is easily observed that we can increase its output by OA/OA’ without increase the input, so its technical efficiency TE= OA/OA’. If we have output price information then we can draw the iso-revenue line A’’C. It is seen from the figure that we can increase the total output revenue by OA’/OA’’ if we move from point A’ to point C without increasing input. So its allocative efficiency AE= OA’/OA’’. Therefore its economic efficiency EE = TE*AE = (OA/OA’) * (OA’/OA’’) = OA/OA’’.

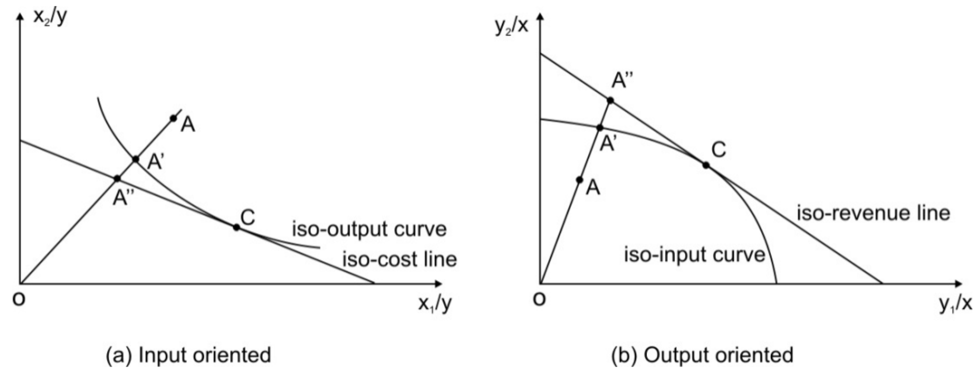


Figure 3.5: Input and output orientated measures.

These efficiency measures assume the production function of the fully efficient firm is known. In practice this is not the case, and the efficient isoquant must be estimated from the sample data.

3.4 Measure University Technology Transfer Efficiency

The above analysis of DEA can be formulated as follows

$$
\begin{aligned}
&\textit{If decision making unit } (DMU)\ i \textit{ uses } x_i \textit{ and produce } y_i, \textit{ then}:\\
&(I)\ \textit{if } j \textit{ uses } x_i \textit{ then}\\
&\quad y_j < y_i \Rightarrow j \textit{ is inefficient}\\
&\quad y_j > y_i \Rightarrow i \textit{ is inefficient}\\
&\quad y_j = y_i \Rightarrow \textit{no evidence that } i \textit{ or } j \textit{ is inefficient};\\
&(II)\ \textit{if } j \textit{ produces } y_i \textit{ then}\\
&\quad x_j > x_i \Rightarrow j \textit{ is inefficient}\\
&\quad x_j < x_i \Rightarrow i \textit{ is inefficient}\\
&\quad x_j = x_i \Rightarrow \textit{no evidence that } i \textit{ or } j \textit{ is inefficient};
\end{aligned}
$$

In order to determine the relative efficiency scores, a linear program (LP) (Vanderbei 2001) must be run for each DMU. Performance Improvement Management (PIM) Software 3.0 is used in my research (Emrouznejad and Thanassoulis 2011). By using a linear objective function, the assumption is made that the efficient frontier is piecewise linear. We consider an output orientation Variable Return to Scale (VRS) model.

$$
Max \sum_{j=1}^{n} \lambda_j y_j
$$

$$
s.t. \begin{cases} \sum_{j=1}^{n} \lambda_j x_j \le x_i \\ \sum_{j=1}^{n} \lambda_j y_j \ge y_i \end{cases}
$$

$$
TE_i = \frac{y_i}{\sum_{j=1}^{n} \lambda_j y_j}
$$

We took a sample of 100 universities/institutions from the Association of University Technology Managers (AUTM) survey 1996-2011. The survey starts from 1991 but we didn't use the data in the first five years because there were not many participating universities and some data, like number of startups initiated, are missing in the early years. In addition, the AUTM survey itself developed in the first five years until its current standardized format. So we believe the data from 1996 to 2011 are better for our analysis and will lead to better insights for university technology transfer practice.

The 100 universities/institutions are selected based on data availability and data significance. Not every university participated each year. If a university/institution failed to participate in the survey for a consecutive 5 years, its data will not be used. If a university/institution's data is not significant enough to be ranked top 100, its data will not be used. Please note there is a lag between some input and output. For instance, license revenue received is from patents awarded in the past. Therefore, we use a 16-year average of the data to reduce error from time lags. We will further study the time lag effect in Chapter 4. It turned out that time lag doesn't affect the overall trend much. Following is a table of the data statistics. LICFTE denotes Number of Full-time Employees in Technology Licensing Office; FEDEXP denotes Federal Funding; LCEXEC denotes Licenses Executed; LIRECD denotes Licenses Income Received; EXPLGF denotes Legal Fee Expenditure; INVDIS denotes Invention Disclosure; USPTIS denotes Number of US Patents Awarded; STRTUP denotes Number of Start-ups Initiated.

Table 3.2: Input and output statistics.

	Mean	**Std. Dev.**	**Min**	**Max**
LICFTE	5.45	6.7	0.94	60.89
FEDEXP	$202,846,644	$239,776,080	$9,002,594	$1,862,061,210
LCEXEC	34.43	36.27	1.45	230.38
LIRECD	$11,845,837	$23,753,720	$56,073	$123,335,332
EXPLGF	$1,680,625	$2,737,702	$125,359	$23,167,584
INVDIS	120.52	138.04	12.75	1132
USPTIS	27.17	35.32	2.46	276.38
STRTUP	3.61	4.05	0.21	30.5

We use the above data in three models: M1 (university research), M2 (technology transfer office), and M3 (university as a whole which include both the research part and technology transfer office). Please see Figure 3.1 for reference of M1, M2, and M3. Input and output of the three models are shown in the following table.

Table 3.3: Input and output of M1, M2, and M3.

	M1		M2		M3	
	Input	Output	Input	Output	Input	Output
FEDEXP	×				×	
INVDIS		×	×			
LICFTE			×		×	
EXPLGF			×		×	
LCEXEC				×		×
LIRECD				×		×
STRTUP				×		×
USPTIS				×		×

By using data envelopment analysis, we assessed the efficiencies of 100 universities as shown in the following table. Note that M1 Efficiency times M2 Efficiency doesn't necessarily equal to M3 Efficiency because they are relative efficiencies rather than absolute efficiencies.

Table 3.4: University technology transfer efficiency 1996-2011.

DMU	University	M1	M2	M3
U01	Arizona State University	45.11%	54.79%	65.09%
U02	Auburn University	33.92%	31.92%	34.02%
U03	Baylor College of Medicine	32.05%	57.28%	61.77%
U04	Boston University	22.55%	92.44%	66.77%
U05	Brigham Young University	83.71%	100.00%	100.00%
U06	California Institute of Technology	100.00%	100.00%	100.00%
U07	Carnegie Mellon University	27.27%	64.60%	64.60%
U08	Case Western Reserve University	13.88%	56.15%	37.36%
U09	Clemson University	31.14%	100.00%	100.00%
U10	Colorado State University	18.98%	54.27%	52.71%
U11	Columbia University	36.89%	100.00%	100.00%
U12	Cornell University	53.44%	100.00%	100.00%
U13	Dartmouth College	11.29%	94.28%	77.47%
U14	Duke University	33.86%	75.38%	68.69%
U15	East Carolina University	100.00%	37.13%	100.00%
U16	Emory University	22.41%	53.48%	40.66%
U17	Florida State University	12.26%	100.00%	100.00%
U18	Georgetown University	22.82%	41.72%	31.24%
U19	Georgia Institute of Technology	46.21%	67.90%	67.38%
U20	Harvard University	31.43%	69.82%	52.95%
U21	Indiana University	22.44%	59.76%	50.14%
U22	Iowa State University	70.66%	100.00%	100.00%
U23	Johns Hopkins University	35.05%	71.70%	71.70%
U24	Kansas State University	45.73%	76.91%	86.23%
U25	Kent State University	35.26%	42.72%	52.22%
U26	Massachusetts Inst. of Technology	69.66%	100.00%	100.00%
U27	Michigan State University	39.29%	100.00%	100.00%
U28	Michigan Technological University	44.50%	45.88%	47.13%
U29	Mississippi State University	23.22%	75.76%	73.63%
U30	Montana State University	13.10%	62.56%	37.55%
U31	New Jersey Institute of Technology	51.27%	37.72%	57.23%
U32	New Mexico State University	8.74%	35.08%	27.67%
U33	New York University	23.18%	84.24%	66.04%
U34	North Carolina State University	44.60%	86.02%	90.22%
U35	North Dakota State University	45.36%	69.78%	100.00%
U36	Northwestern University	27.64%	71.17%	61.08%
U37	Ohio State University	24.56%	76.81%	64.25%
U38	Ohio University	48.73%	61.52%	100.00%
U39	Oklahoma State University	16.71%	54.67%	34.00%
U40	Oregon Health Sciences University	22.64%	72.85%	61.70%
U41	Oregon State University	14.30%	65.30%	41.15%
U42	Penn State University	44.84%	100.00%	100.00%
U43	Purdue University	54.36%	84.17%	94.40%
U44	Rice University	8.42%	100.00%	100.00%
U45	Rutgers	46.09%	64.72%	74.40%
U46	Stanford University	50.58%	100.00%	100.00%
U47	State University of New York	48.10%	85.14%	85.14%
U48	Temple University	37.98%	56.73%	58.86%
U49	Texas A&M University System	35.97%	78.89%	79.73%
U50	Tufts University	24.16%	48.43%	36.44%
U51	Tulane University	17.09%	97.37%	84.15%
U52	Univ. of Akron	100.00%	76.80%	100.00%
U53	Univ. of Arizona	29.89%	77.20%	77.20%
U54	Univ. of Arkansas	33.84%	52.95%	59.76%
U55	Univ. of California System	100.00%	100.00%	100.00%
U56	Univ. of Cincinnati	30.49%	58.12%	51.22%
U57	Univ. of Colorado	26.73%	77.42%	77.02%
U58	Univ. of Connecticut	31.89%	51.89%	48.26%
U59	Univ. of Dayton Research Institute	22.64%	68.61%	55.35%
U60	Univ. of Delaware	21.10%	74.92%	71.16%
U61	Univ. of Florida	35.97%	100.00%	100.00%
U62	Univ. of Georgia	32.56%	100.00%	100.00%
U63	Univ. of Hawaii	9.91%	48.83%	22.72%
U64	Univ. of Idaho	39.91%	39.84%	42.16%
U65	Univ. of Illinois Urbana Champaign	26.52%	100.00%	100.00%
U66	Univ. of Iowa	25.84%	60.46%	50.52%
U67	Univ. of Kansas	39.60%	71.85%	68.61%
U68	Univ. of Kentucky	34.30%	69.69%	67.22%
U69	Univ. of Louisville	31.42%	100.00%	100.00%
U70	Univ. of Maryland Baltimore	33.77%	35.66%	32.07%
U71	Univ. of Maryland College Park	34.88%	95.96%	100.00%
U72	Univ. of Massachusetts	30.36%	100.00%	100.00%
U73	Univ. of Miami	14.29%	75.07%	53.14%
U74	Univ. of Michigan	35.00%	74.28%	67.89%
U75	Univ. of Minnesota	45.00%	99.38%	99.14%
U76	Univ. of Nebraska	41.55%	78.25%	89.63%
U77	Univ. of New Hampshire	7.05%	100.00%	100.00%
U78	Univ. of New Mexico	25.31%	65.39%	50.69%
U79	Univ. of North Carolina	26.94%	78.99%	72.66%
U80	Univ. of Oklahoma	28.36%	76.41%	82.00%
U81	Univ. of Oregon	11.54%	100.00%	95.07%
U82	Univ. of Pennsylvania	42.09%	76.74%	67.59%
U83	Univ. of Pittsburgh	14.77%	62.98%	37.98%
U84	Univ. of Rhode Island	15.09%	60.40%	51.87%
U85	Univ. of Rochester	17.36%	64.50%	64.50%
U86	Univ. of South Alabama	31.68%	30.84%	32.63%
U87	Univ. of South Carolina	19.73%	31.79%	24.75%
U88	Univ. of South Florida	36.73%	73.57%	79.40%
U89	Univ. of Southern California	26.93%	73.13%	72.56%
U90	Univ. of Tennessee	36.81%	43.66%	41.59%
U91	Univ. of Utah	56.80%	92.47%	93.38%
U92	Univ. of Virginia	26.19%	56.89%	54.32%
U93	Univ. of Washington	50.41%	100.00%	100.00%
U94	Univ. of Wisconsin-Madison	50.79%	100.00%	100.00%
U95	Vanderbilt University	22.71%	80.84%	80.84%
U96	Virginia Tech	41.01%	100.00%	100.00%
U97	Wake Forest University	24.07%	46.79%	37.11%
U98	Washington State University	26.74%	63.41%	63.19%
U99	Washington University	9.01%	100.00%	66.94%
U100	Wayne State University	26.48%	71.52%	58.06%

Let's further study this problem by drawing efficiency frontiers. Figure 3.6 is the efficiency frontier of M1. M1 has one input federal funding (FEDEXP) and one output invention disclosure (INVDIS). Every red dot is a decision making unit (DMU), which is the research part of a university in this model. The dot highlighted by yellow is Harvard University. It is not on the frontier which means it is inefficient.

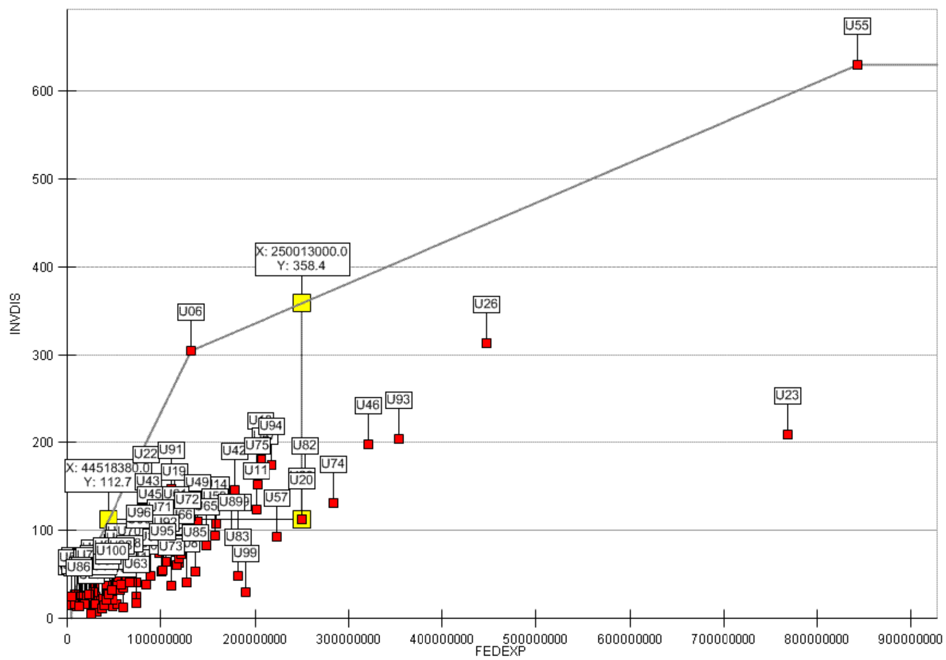


Figure 3.6: Efficiency frontier of M1 (FEDEXP, INVDIS) 1996-2011.

M2 has three inputs and four outputs so its efficiency frontier should be a surface in a seven dimensions space, which cannot be visually illustrated here. Some of the cross sections are shown here. In Figure 3.7, we illustrate the efficiency frontier of one input: number of full-time technology transfer office employees (LICFTE) and two outputs: number of licenses executed (LCEXEC) and license revenue received (LIRECD). Every red dot is a decision making unit (DMU), which is the technology transfer office of a university in this model. The dot highlighted by yellow is Harvard University. Figure 3.8 illustrates the efficiency frontier of one input: legal expenditure (EXPLGF) and two outputs: number of licenses executed (LCEXEC) and license revenue received (LIRECD). Every red dot is a decision making unit (DMU), which is the technology transfer office of a university in this model. The dot highlighted by yellow is Harvard University.

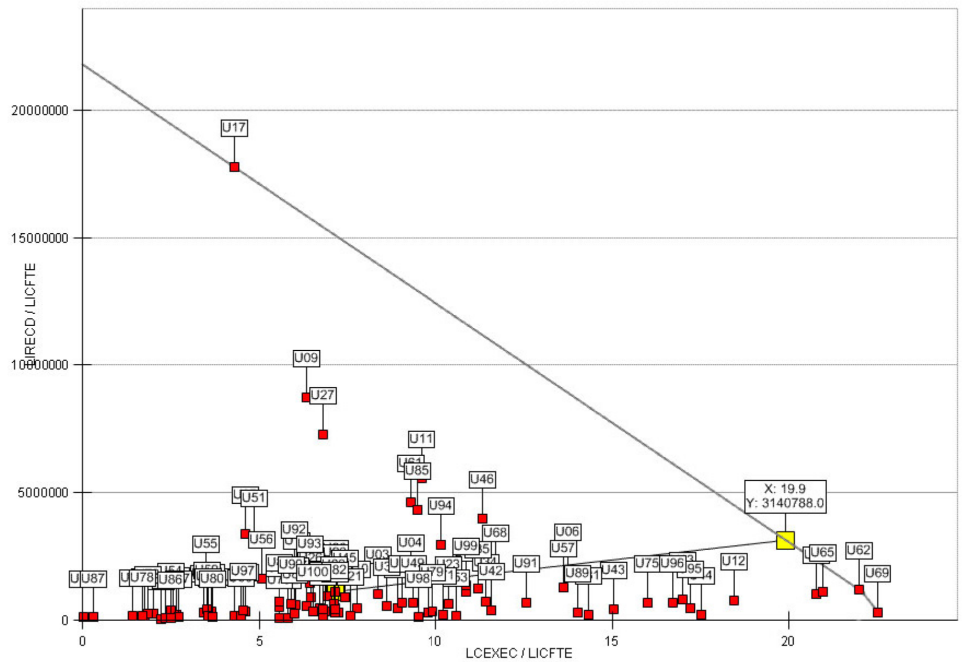


Figure 3.7: Efficiency frontier of M2 (LICFTE, LCEXEC, LIRECD) 1996-2011.

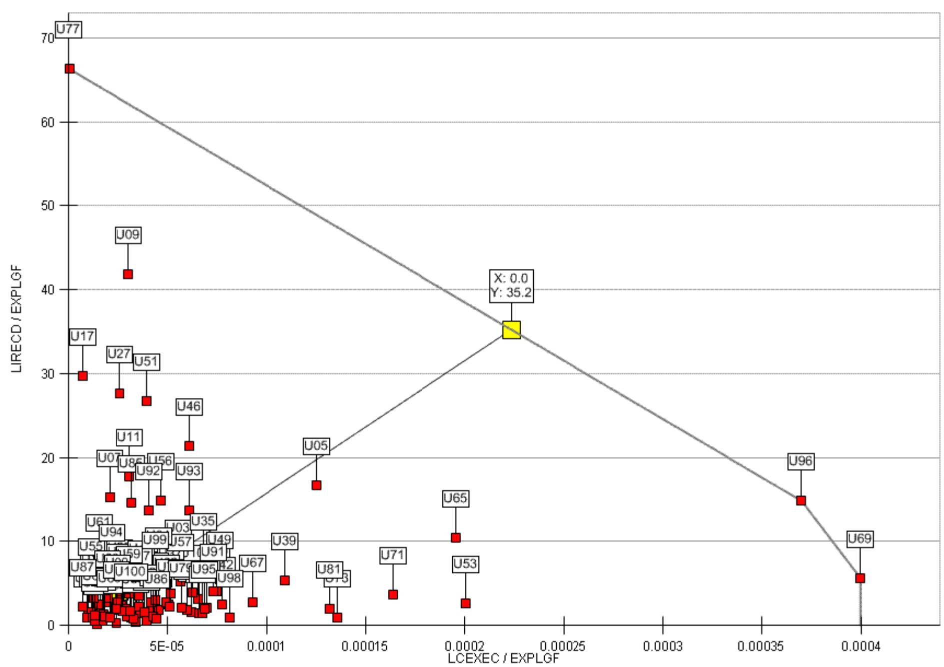


Figure 3.8: Efficiency frontier of M2 (EXPLGF, LCEXEC, LIRECD) 1996-2011.

Figure 3.9 illustrates the efficiency frontier of one input: invention disclosure (INVDIS) and two outputs: number of licenses executed (LCEXEC) and license revenue received (LIRECD). Every red dot is a decision making unit (DMU), which is the technology transfer office of a university in this model. The dot highlighted by yellow is Harvard University. Figure 3.10 illustrates the efficiency frontier of one input: number of full-time technology transfer office employees (LICFTE) and two outputs: number of US patents awarded (USPTIS) and number of start-ups initiated (STRTUP). Every red dot is a decision making unit (DMU), which is the technology transfer office of a university in this model. The dot highlighted by yellow is Harvard University. Figure 3.11 illustrates the efficiency frontier of one input: legal fee expenditure (EXPLGF) and two outputs: number of US patents awarded (USPTIS) and number of start-ups initiated (STRTUP). Every red dot is a decision making unit (DMU), which is the technology transfer office of a university in this model. The dot highlighted by yellow is Harvard University.

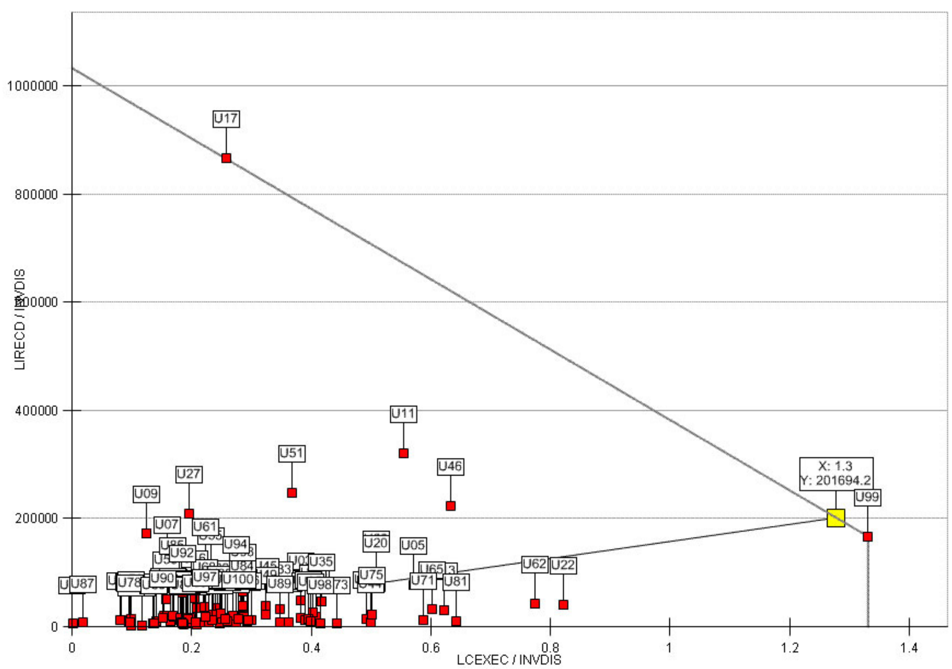


Figure 3.9: Efficiency frontier of M2 (LICFTE, LCEXEC, LIRECD) 1996-2011.

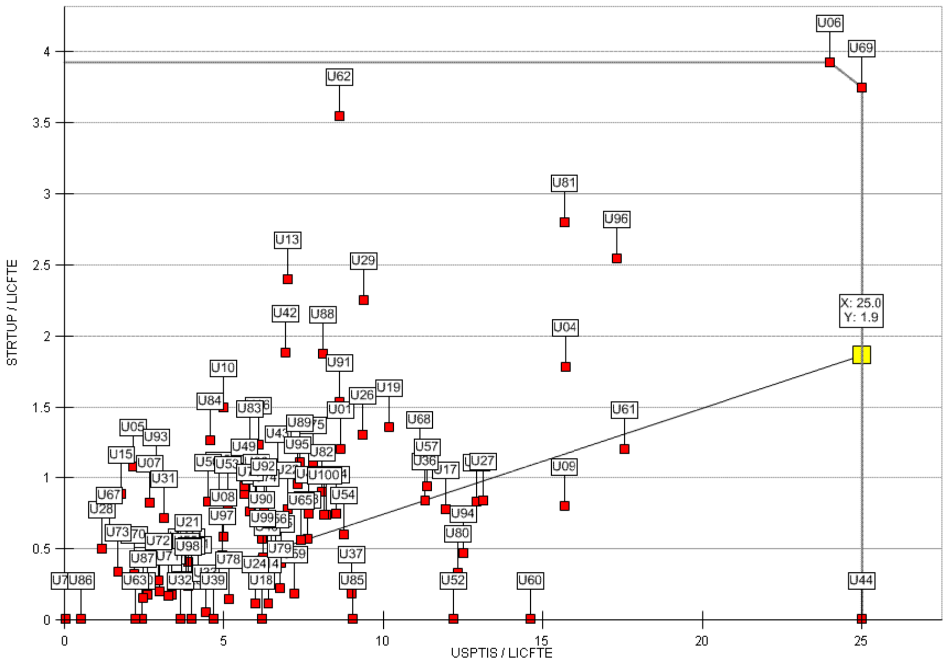


Figure 3.10: Efficiency frontier of M2 (LICFTE, USPTIS, STRTUP) 1996-2011.

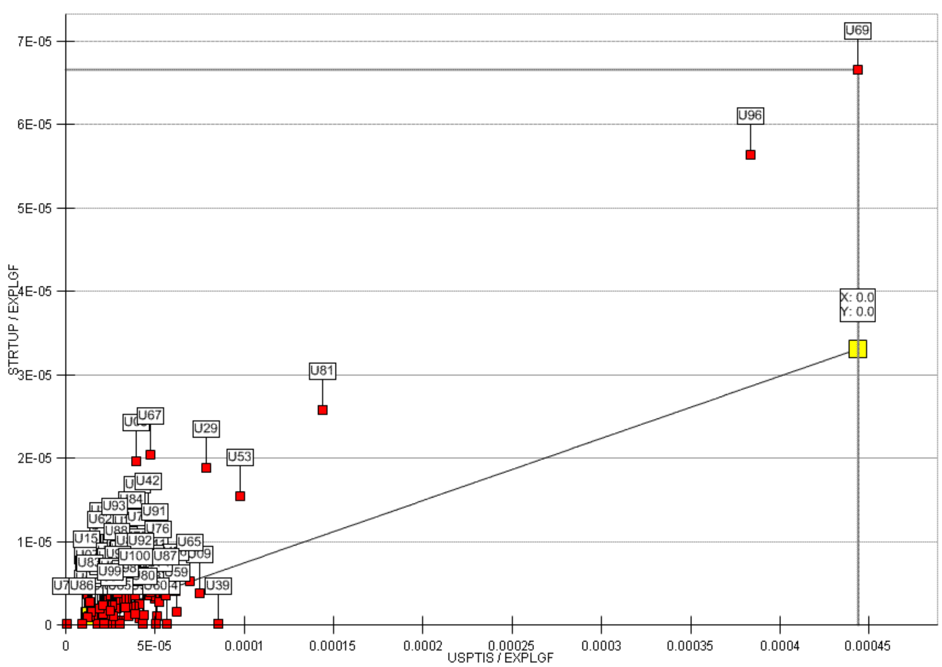


Figure 3.11: Efficiency frontier of M2 (EXPGF, USPTIS, STRTUP) 1996-2011.

M3 has three inputs and four outputs so its efficiency frontier should be a surface in a seven dimensions space, which cannot be visually illustrated here. Some of the cross sections are shown here. In Figure 3.12, it illustrates the efficiency frontier of one input: federal funding (FEDEXP) and two outputs: number of licenses executed (LCEXEC) and license revenue received (LIRECD). Every red dot is a decision making unit (DMU), which is the technology transfer office of a university in this model. The dot highlighted by yellow is Harvard University.

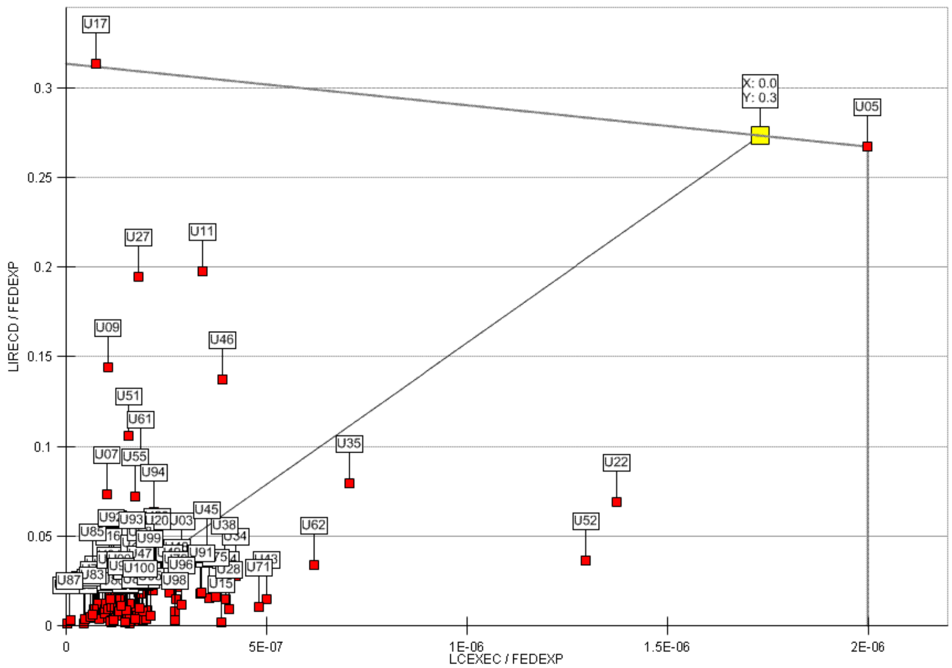
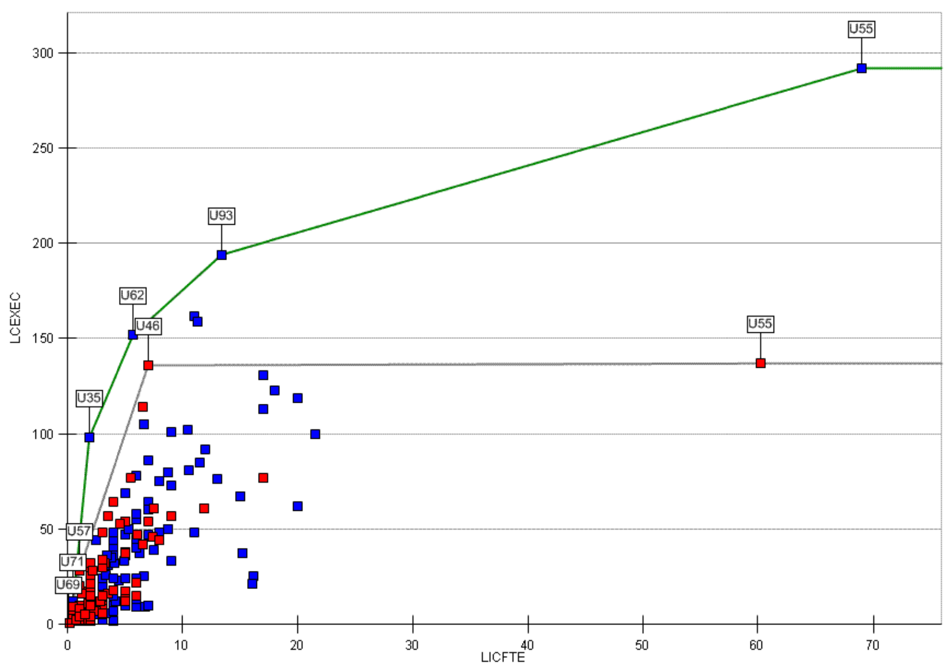


Figure 3.12: Efficiency frontier of M3 (FEDEXP, LCEXEC, LIRECD) 1996-2011.

3.5 Measure Year to Year Productivity Changes - Malmquist Index

The above analysis measures average efficiency between 1996 and 2011 but don't measure year to year efficiency changes. As shown in the following figure, the grey line is the 1996 efficiency frontier and the green line is the 2011 efficiency frontier. The green line shifted outwards from the grey line, which means more output are produced with the same amount of input. This is called Technical Change (TC) of the efficiency. Meanwhile, most of the red dots are away from the efficient frontier and the blue dots are closer to the frontier, which means inefficient DMUs are more efficient than before and gradually catch up with the efficient DMUs. This is called Efficiency Catching-up (EC) (Färe et al. 1994).



Red dots are DMUs in 1996 and grey line is their efficient frontier while blue dots are DMUs in 2011 and green line is their efficient frontier.

Figure 3.13: Year to year efficiency change.

The above figure is an intuitive way to show the year to year efficiency change. Malmquist index will be used to quantitatively measure year to year efficiency changes at DMU level. The Malmquist Index (MI) is a bilateral index that can be used to compare the production technology of two organizations (Caves, Christensen and Diewert, 1982). Suppose there are two organizations A with the production function $f_A(\bullet)$ and B with the production function $f_B(\bullet)$. In order to compare the productivity difference between A and B, we calculate the Malmquist Index (MI). Specifically, we substitute the inputs of economy A into the production function of B, and vice versa. The Malmquist index of A with respect to B is the geometric mean of $\frac{f_A(A)}{f_A(B)}$ and $\frac{f_B(A)}{f_B(B)}$,

$$MI_{A/B} = \sqrt{\frac{f_A(A)}{f_A(B)} * \frac{f_B(A)}{f_B(B)}}, \text{ where}$$

$f_A(A)$ is the production function of A with input A

$f_A(B)$ is the production function of A with input B

$f_B(A)$ is the production function of B with input A

$f_B(B)$ is the production function of B with input B

Note that the MI of A with respect to B is the reciprocal of the MI of B with respect to A. If the MI of A with respect to B is greater than 1, the productivity of A is superior to that of B. Then in our research, the technology transfer efficiency MI of 1997 with respect to 1996 is

$$MI_{1997/1996} = \sqrt{\frac{f_{1997}(Input_{1997})}{f_{1997}(Input_{1996})} * \frac{f_{1996}(Input_{1997})}{f_{1996}(Input_{1996})}}$$

To better understand the efficiency change, we not only calculate MI but also decompose MI into Technical Change (TC) and Efficiency Catching-up (EC) to see which element the changes are attributed to.

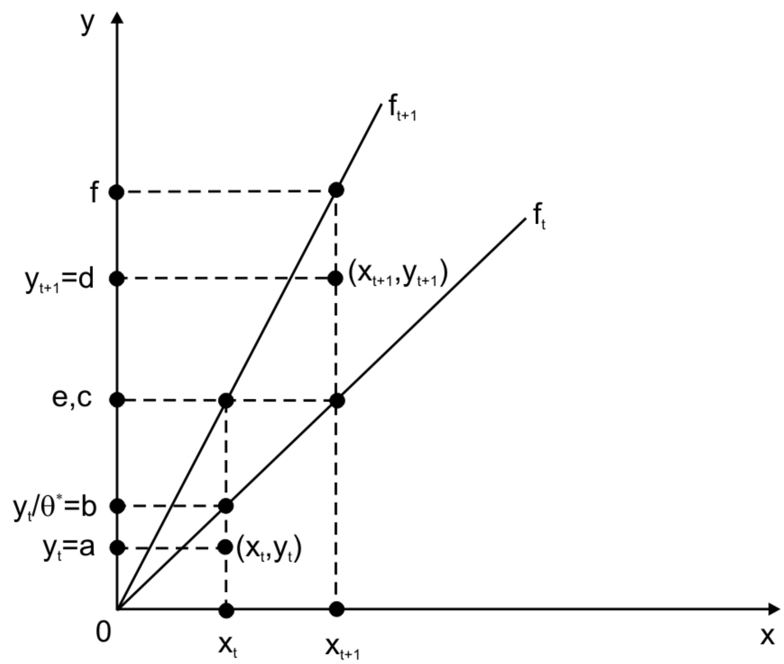


Figure 3.14: Malmquist index decomposition (Färe et al. 1994).

Figure 3.14 shows the decomposition of Malmquist index for constant return to scale. f_t and f_{t+1} are the production functions of time t and time t+1, respectively.

$$MI(x_{t+1}, y_{t+1}, x_t, y_t) = \sqrt{\left(\frac{f_{t+1}(x_{t+1}, y_{t+1})}{f_{t+1}(x_t, y_t)}\right)\left(\frac{f_t(x_{t+1}, y_{t+1})}{f_t(x_t, y_t)}\right)}$$

$$= \frac{f_{t+1}(x_{t+1}, y_{t+1})}{f_t(x_t, y_t)} \times \sqrt{\left(\frac{f_t(x_{t+1}, y_{t+1})}{f_{t+1}(x_{t+1}, y_{t+1})}\right)\left(\frac{f_t(x_t, y_t)}{f_{t+1}(x_t, y_t)}\right)}$$

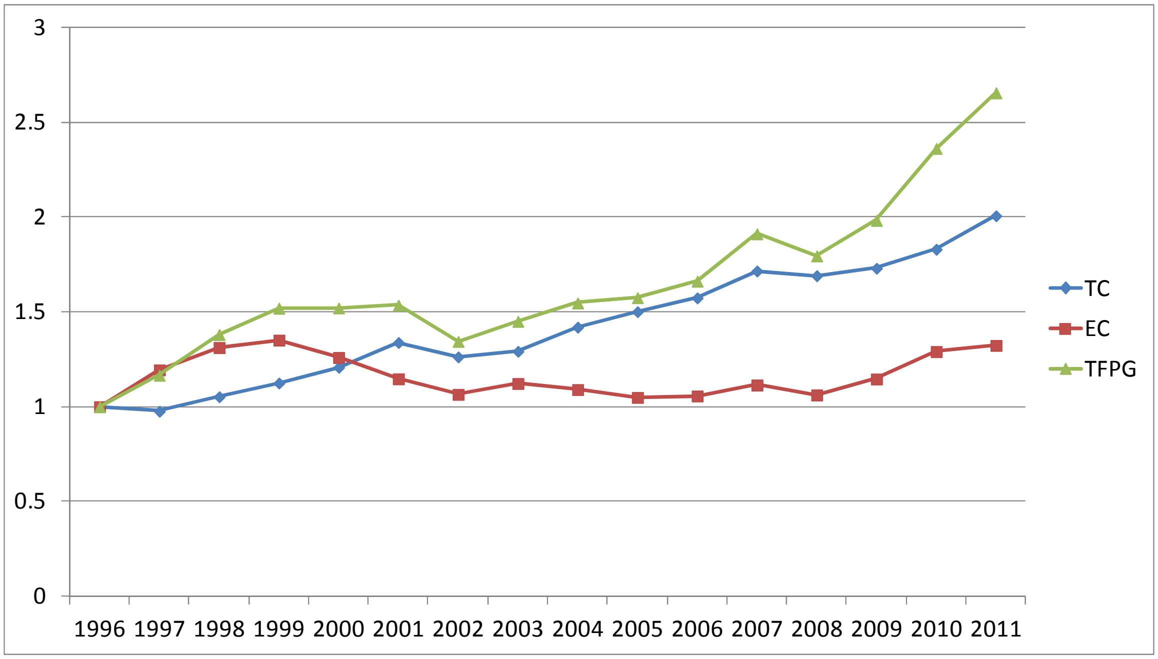
$$\text{efficiency change} = \frac{f_{t+1}(x_{t+1}, y_{t+1})}{f_t(x_t, y_t)}$$

$$\text{technical change} = \sqrt{\left(\frac{f_t(x_{t+1}, y_{t+1})}{f_{t+1}(x_{t+1}, y_{t+1})}\right)\left(\frac{f_t(x_t, y_t)}{f_{t+1}(x_t, y_t)}\right)}$$

In terms of distances in the figure,

$$\begin{aligned} & MI(x_{t+1}, y_{t+1}, x_t, y_t) \\ &= \left(\frac{0d}{0f}\right)\left(\frac{0b}{0a}\right)\sqrt{\left(\frac{0d/0e}{0d/0f}\right)\left(\frac{0a/0b}{0a/0c}\right)} \\ &= \left(\frac{0d}{0f}\right)\left(\frac{0b}{0a}\right)\sqrt{\left(\frac{0f}{0e}\right)\left(\frac{0c}{0b}\right)} \end{aligned}$$

Then we use data from AUTM survey 1996-2011 to calculate the Malmquist Index decomposition from year to year: 1997/1996, 1998/1997, 1999/1998, 2000/1999, 2001/2000, 2002/2001, 2003/2002, 2004/2003, 2005/2004, 2006/2005, 2007/2006, 2008/2007, 2009/2008, 2010/2009, 2011/2010. The result is shown in the figure below. It is observed that Total Factor Productivity Growth (TFPG) in 2011 is about 2.7 times that of 1996 with a Compound Annual Growth Rate (CAGR) of 6.7%. Efficiency Catching-up has a Compound Annual Growth Rate of 1.8% and Technical Change (TC) has a Compound Annual Growth Rate of 4.7%. Therefore, the productivity growth has stemmed primarily from a growth in commercialization by all universities rather than a catching up by the inefficient universities.



TC: Technical Change; EC: Efficiency Catching-up; TFPG (MI): Total Factor Productivity Growth

Figure 3.15: Malmquist index decomposition 1996-2011 (M3).

3.6 Technology Transfer and Academic Reputation

Universities have many other goals besides transferring their academic discoveries to the economy. Then are academic reputation and technology transfer efficiency correlated? We studied the technology transfer efficiency score 2006-2011 (M3 score) and academic score data from US News National University Rankings 2012. Both of the scores are between 0 and 1. University academic score doesn't change much within a period of several years so it's still valid to use it with technology transfer efficiency scores from a different year. As is shown in the following figure, blue dots denote academic scores of the 100 Universities in ascending order and red dots denote their corresponding efficiency scores. It is observed that the red dots are all over the place, meaning there is no obvious correlation between the academic score and efficiency score.

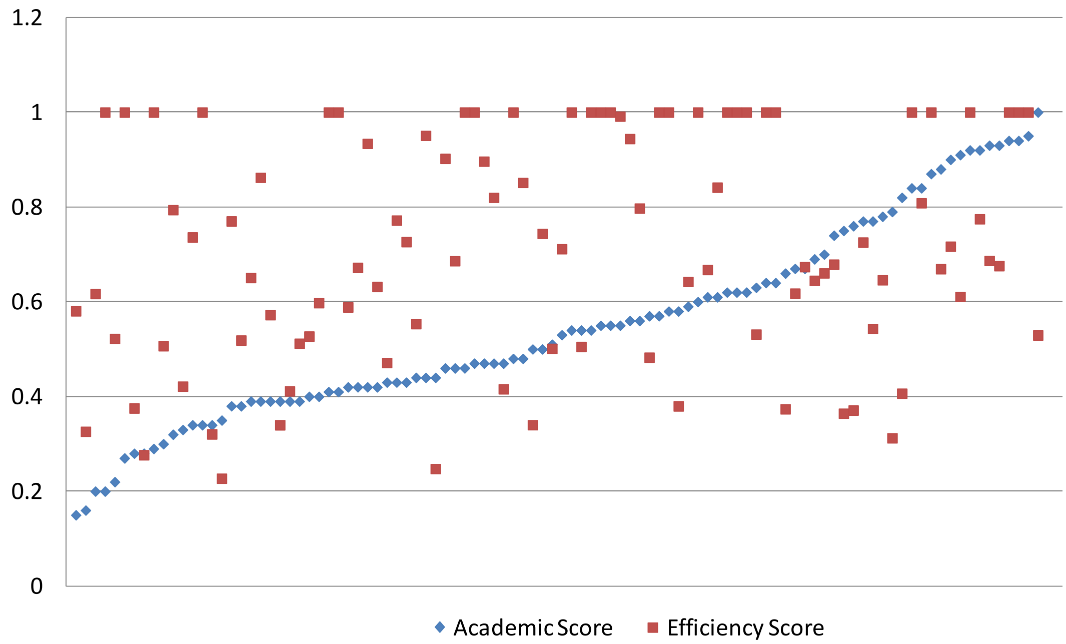


Figure 3.16: Technology transfer efficiency score and academic reputation score.

We further study the relationship between them by running regression for both academic score and efficiency score as shown in Table 3.4 and Table 3.5. In either case, the regression coefficient is not significant as we can see from the T test for the regression coefficient. Usually in a T test, if P value is less than 0.05 (and sometimes 0.01), we say regression coefficient is significant, meaning the two variables have significant correlation. However, in Table 3.4 and Table 3.5, both the P values are 0.11. So we cannot say the two variables have significant correlation. It doesn't mean the two absolutely don't have any correlation. It means they don't have significant correlation.

Table 3.5: Regression of Efficiency Score and T test for regression coefficient

Source	SS	df	MS		
				Number of obs =	100
				F(1 , 98) =	2.61
Model	0.1087353	1	0.1087353	Prob > F =	0.1097
Residual	4.0903397	98	0.0417382	R-squared =	0.0259
				Adj R-squared =	0.0160
Total	4.199075	99	0.0424149	Root MSE =	0.2043

Aca Score	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Eff Score	0.1393375	0.0863275	1.61	0.11	-.0319767	.3106516
Intercept	0.4493479	0.0647385	6.94	0	.3208764	.5778194

Table 3.6: Regression of Academic Score and T test for regression coefficient

Source	SS	df	MS		
				Number of obs =	100
				F(1 , 98) =	2.61
Model	0.1450279	1	0.1450279	Prob > F =	0.1097
Residual	5.4555735	98	0.0556691	R-squared =	0.0259
				Adj R-squared =	0.0160
Total	4.199075	99	0.0424149	Root MSE =	0.2359

Eff Score	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Aca Score	0.1858442	0.1151411	1.61	0.11	-.0426496	.4143379
Intercept	0.6096615	0.0674183	9.04	0	.475872	.743451

Insights to university policy makers and people: a university with lower technology transfer efficiency is not an evidence of academic inferior to other universities with higher technology transfer efficiency. A university with higher technology transfer efficiency is not superior to other university with lower technology transfer efficiency.

Chapter 4 University Research Portfolio Management

4. 1 Modern Portfolio Theory

Modern portfolio theory (MPT) (Elton 2010) (Modern portfolio theory Wikipedia 2013) is a theory in finance that attempts to reduce portfolio risk by carefully choosing the proportions of various assets. Modern Portfolio Theory was introduced in 1952 by Harry Markowitz (Markowitz 1952), who received a Nobel Prize in economics in 1990. MPT was considered an important advance in the mathematical modeling of finance. In the 1970s, concepts from Modern Portfolio Theory were used by Michael Conroy to model the labor force in the economy in the field of regional science (Conroy 1975). Recently, modern portfolio theory has been used to model the self-concept in social psychology (Chandra and Shadel 2007). More recently, modern portfolio theory has been applied to modeling the uncertainty and correlation between documents in information retrieval (Wang and Zhu 2009) or even has been applied to the analysis of terrorism (Phillips 2009). In our research, MPT was applied to modeling the uncertainty and return in university research portfolio management and technology transfer for the first time.

Like any other theory in economics or even natural sciences, MPT got theoretical and practical criticisms over the years. These include the fact that financial returns do not follow a Gaussian distribution, and that correlations between asset classes are not fixed but can vary depending on external events (Kat 2002). Further, MPT assumes that investors are rational and markets are efficient but there is growing evidence that they are not (Shleifer 2003). That said, MPT is still the best tool to model uncertainty and return for a utility maximizing agent but cautions must be used when making assumptions and conclusions.

Basically, MPT is a mathematical formulation of the concept of diversification in investing, with the goal of structuring a portfolio of assets that has collectively lower risk than any individual asset. Intuitively speaking, by combining different assets that change in value in opposite ways, we can reduce the portfolio overall risk. Even if returns of the assets are positively correlated, proper diversification can lower the overall risk. MPT uses a Gaussian distribution function to model the return of an asset, and use the standard deviation of the return to model its risk. A portfolio is a weighted combination of the assets. So the return of a portfolio is the weighted combination of the assets' returns. By combining different assets whose returns are not perfectly positively correlated, MPT seeks to reduce the total variance of the portfolio return.

Mathematically, utility-maximizing economic agents attempt to maximize the utility function

$$U = f(E_R, \sigma_R)$$

The larger the return the higher the utility and the larger the risk the lower the utility, so we have

$$\frac{dU}{dE_R} > 0$$

$$\frac{dU}{d\sigma_R} < 0$$

Where U the agent's total utility, E_R is the expected return of a portfolio and σ_R is the standard deviation of the possible divergence of actual returns from expected returns (Sharpe 1964). Markowitz (Markowitz 1952) was among the first to realize that agents do not care solely about the return of a portfolio. Risk averse agents also care about the risk of the portfolio. Markowitz's definition of risk as the variability of returns (measured by variance or standard deviation) has long been accepted in financial economics. Geometrically, the indifference curves that derive from this particular configuration of risk averse individual's utility are concave-upwards in the expected return-risk plane as displayed in Figure 4.1.

Like most parts of economic theory, modern portfolio theory involves economic agents attempting to maximize utility by making choices. In the context of modern portfolio theory, a utility maximizing agent has to make a choice of its portfolio composition. For every possible portfolio we compute the expected return and variance.

Formally, the expected return on a portfolio is given by

$$E(R_P) = \sum_{i=1}^{n} w_i E(R_i)$$

where w_i is the proportion of total investment in asset i, $E(R_i)$ is the expected return on asset i, and $\sum_{i=1}^{n} w_i = 1$. The mean historic return is usually used as a proxy for the return that is expected in the future.

The risk (variance) of a portfolio is

$$\sigma_P^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j Cov_{ij} = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \rho_{ij}\sigma_i\sigma_j = \sum_{i=1}^{n} w_i^2\sigma_i^2 + \sum_{i=1}^{n}\sum_{\substack{j=1 \\ i\neq j}}^{n} w_i w_j \rho_{ij}\sigma_i\sigma_j$$

where Cov_{ij} is the covariance between assets i and j

ρ_{ij} is the correlation coefficient that measures the correlation between assets i and j.

$$Cov_{ij} = \rho_{ij}\sigma_i\sigma_j$$

By computing the return and risk for all the possible portfolios, we get the following figure. The dashed lines are indifference curves with utility $U_0 < U_1 < U_2 < U_3 < U_4$, every point on the same curve has the same utility so it's indifferent in terms of utility. Under the assumption of risk aversion, the indifference curves are concave-up facing northwest because we don't like risk and higher risk has to be compensated by higher return. The solid curve is the efficient frontier, which is the set of all possible portfolios. Obviously, a utility-maximizing agent should choose point P, which has the highest utility among all possible portfolios.

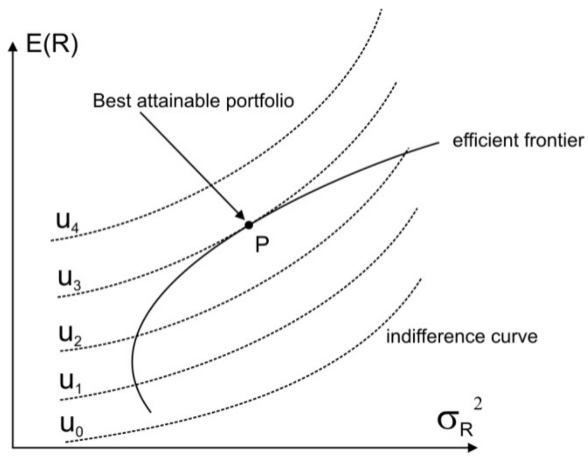


Figure 4.1: Indifference curve and efficient frontier.

4.2 Modeling University Research Portfolio

4.2.1 Assumptions and Definitions

As we know, a University has research in many disciplines that produce scientific discovery and inventions. Every discipline is an asset a university can invest in. University research portfolio management is all about allocating university resource, funding, faculty, space, and etc. in different disciplines. University management makes decisions to structure research disciplines, for instance, to expand or downsize a discipline, to support or not to support a department, to recruit more professors in a discipline or not. The decisions are made based on many factors like school tradition, endowment, federal and private funding, students and employers' demand, and etc. It’s a decision under uncertainty because we don’t know the exact output of a discipline in the future although we could predict from the past. But there are uncertainties so there is a risk involved. This is the reason we need to use Modern Portfolio Theory. It will provide insights for university management when making decisions on research structure and will also address the question in the beginning of this thesis if we can increase technology transfer output by properly structure university research portfolio.

Conceivably, technology transfer efficiency is correlated to university research portfolio. Some universities have more engineering and applied sciences research and will produce more inventions with commercial value while some universities have more basic scientific research that result in less inventions with commercial value. To provide insights for university management, we have to quantitatively study the relationship between technology transfer efficiency and research portfolio. Therefore, we use Modern Portfolio Theory. It is the first time Modern Portfolio Theory is applied in modeling university research portfolio.

First of all, some assumptions and definitions are made.

Assumption 1

The axioms of expected utility or rational choice apply to University research and technology transfer.

Assumption 2

The economic good is solely a function of the expected return and risk (variance) associated with particular combinations (portfolios) of research disciplines.

Definition 1

The expected return of federal funding research is the number of patents. (This is discussed in detail in section 4.3)

Definition 2

The risk of federal funding research is the standard deviation of the possible divergence of actual returns from expected returns.

4.2.2 A Two-disciplines Case

Let's start with a simple two-disciplines case.

Discipline A with return R_A and $RISK(A) = Var(A) = \sigma_A^2$

Discipline B with return R_B and $RISK(B) = Var(B) = \sigma_B^2$

A research portfolio P is a combination of A and B with weights w_A and w_B, $0 \le w_A, w_B \le 1$, then the return of the portfolio is $R_P = w_A R_A + w_B R_B$, and risk is

$$RISK(P) = Var(P) = w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + 2w_A w_B Cov(A,B) = w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + 2w_A w_B \rho_{AB}\sigma_A\sigma_B$$

ρ_{AB} measures the correlation (linear dependence) between discipline A and B, $-1 \le \rho_{AB} \le 1$. $\rho_{AB} = 1$ implies that a linear equation describes the relationship between A and B perfectly, with all data points lying on a line for which B increases as A increases. $\rho_{AB} = -1$ implies that all data points lie on a line for which B decreases as A increases. $\rho_{AB} = 0$ implies that there is no linear correlation between the variables. $-1 < \rho_{AB} < 0$ and $0 < \rho_{AB} < 1$ imply that the positive or negative linear dependence is not perfect. All the above cases are illustrated in Figure 4.2.

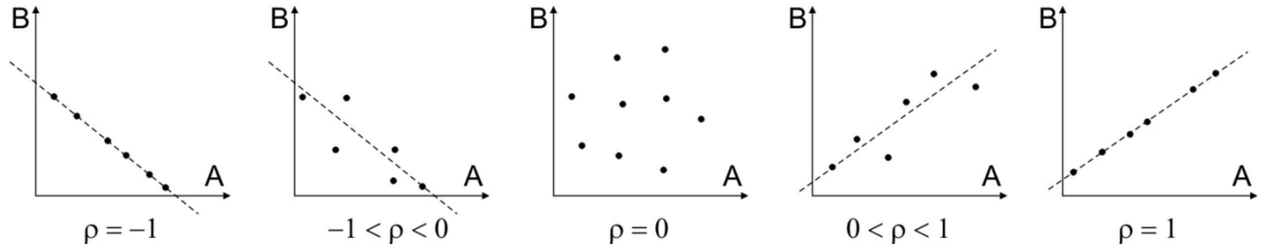


Figure 4.2: Correlation coefficient.

Let's see an example with $R_A = 0.2, \sigma_A^2 = 0.2$; $R_B = 0.8, \sigma_B^2 = 0.5$; $\rho_{AB} = -0.3$. We vary the combination of A and B by varying the weights of A and B $0 \le w_A, w_B \le 1$ *and* $w_A + w_B = 1$. The risk and return curve is shown in Figure 4.3. At point A, $w_A = 1, w_B = 0$, which means the portfolio has only discipline A and no discipline B, so naturally risk=0.2 and return=0.2. Meanwhile at point B, $w_A = 0, w_B = 1$, which means the portfolio has only discipline B and no discipline A, so naturally risk=0.5 and return=0.8. At point X, $w_A = 0.8, w_B = 0.2$, which means the portfolio consists of 80% discipline A and 20% discipline B. So the portfolio return and risk are:

$$R_P = w_A R_A + w_B R_B = 0.8*0.2 + 0.2*0.8 = 0.32$$

$$RISK(P) = Var(P) = w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + 2w_A w_B Cov(A,B) = w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + 2w_A w_B \rho_{AB}\sigma_A\sigma_B = 0.16$$

Please note point X has larger return and lower risk than point A, which means by adding some discipline B, we not only increased return but also reduced risk. This result sounds very exciting.

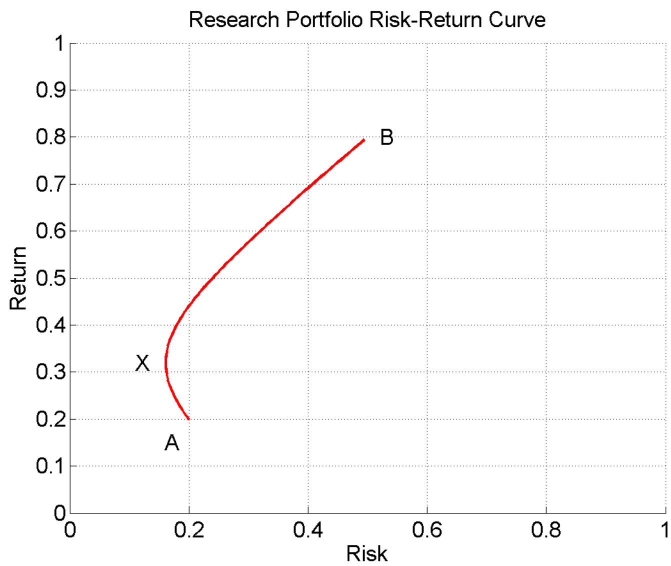


Figure 4.3: Research portfolio risk-return curve for a 2-disciplines case.

For an extreme case, when $\rho = -1$, point X will be on the vertical axis so we can attain a return higher than point X with risk=0, which is shown in the figure below.

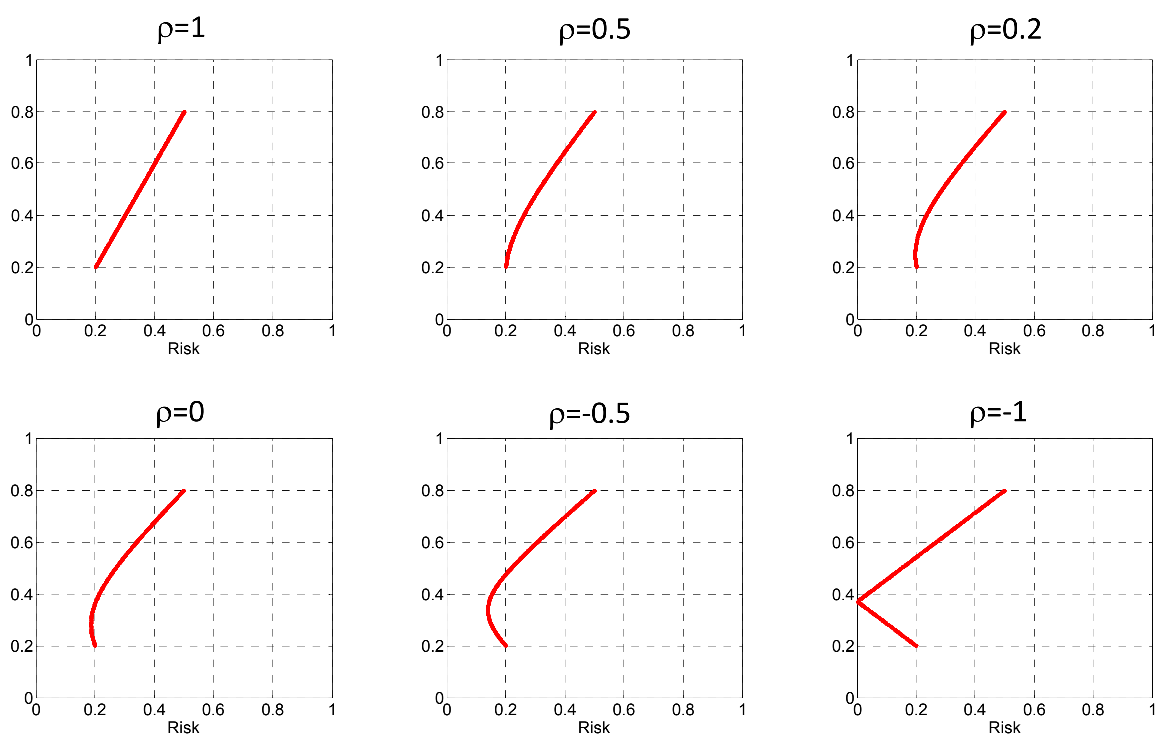


Figure 4.4: Risk-return curve of portfolios with two hypothetical disciplines.

We learned from the above case that diversification helps to reduce the overall portfolio risk. It's based on imperfect correlation among different disciplines.

4.2.3 A Three-disciplines Case

For a three-disciplines case, suppose we have three disciplines A, B, and C. Their return, risk, and correlation matrix are shown in the tables below.

Table 4.1: Three disciplines A, B, and C.

	Return	Risk	Weight
Discipline A	$R_A = 0.1$	$\sigma_A^2 = 0.2$	w_A
Discipline B	$R_B = 0.3$	$\sigma_B^2 = 0.5$	w_B
Discipline C	$R_C = 0.8$	$\sigma_C^2 = 0.6$	w_C
Portfolio	R_P	σ_P^2	

Table 4.2: Correlation matrix of three disciplines.

	Discipline A	Discipline B	Discipline C
Discipline A	1	0.5	0.4
Discipline B	0.5	1	0.6
Discipline C	0.4	0.6	1

Then its portfolio return and risk are calculated as:

$$R_P = w_A R_A + w_B R_B + w_C R_C$$

$$\begin{aligned}\sigma_P^2 &= w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + w_C^2\sigma_C^2 + 2w_A w_B Cov(A,B) + 2w_B w_C Cov(B,C) + 2w_A w_C Cov(A,C)\\ &= w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + w_C^2\sigma_C^2 + 2w_A w_B \rho_{AB}\sigma_A\sigma_B + 2w_B w_C \rho_{BC}\sigma_B\sigma_C + 2w_A w_C \rho_{AC}\sigma_A\sigma_C\end{aligned}$$

$$\begin{cases}-1 \le \rho_{AB}, \rho_{BC}, \rho_{AC} \le 1\\ 0 \le w_A, w_B, w_C \le 1\\ w_A + w_B + w_C = 1\end{cases}$$

By varying w_A, w_B, w_C while keeping one of them 0, we get the following frontier. Any possible portfolio constructed by A, B, and C should be within the triangle curve.

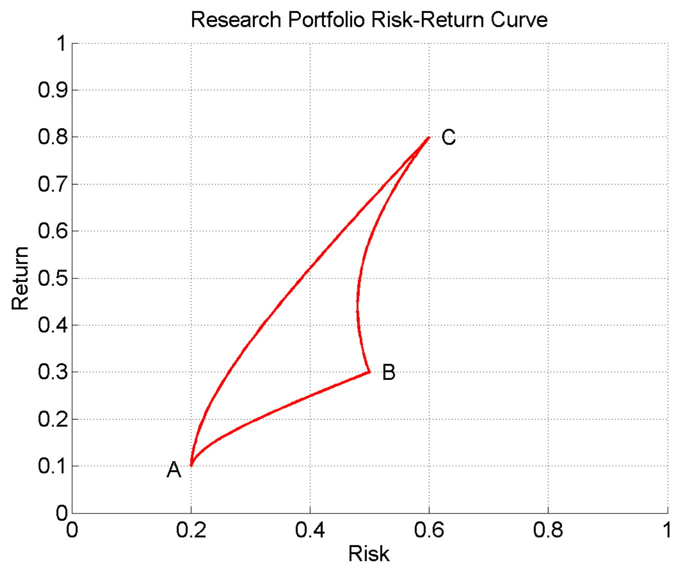


Figure 4.5: Research portfolio risk-return curve.

Once we have the model ready, we use the data from National Research Council's A Data-Based Assessment of Research-Doctorate Programs in the United States. It has data from 5,004 doctoral programs at 212 universities for the academic year 2005-2006. We categorize these programs into three major disciplines: Engineering, Physical and Mathematical Sciences, and Biological and Life Sciences as shown in the following table.

Table 4.3: Three major disciplines: Engineering, Physical and Mathematical Sciences, and Biological and Life Science

Engineering	Aerospace Engineering
	Biomedical Engineering and Bioengineering
	Chemical Engineering
	Civil and Environmental Engineering
	Computer Engineering
	Electrical and Computer Engineering
	Engineering Science and Materials
	Materials Science and Engineering
	Mechanical Engineering
	Operations Research, Systems Engineering and Industrial Engineering
Physical and Mathemetical Sciences	Applied Mathematics
	Astrophysics and Astronomy
	Chemistry
	Computer Sciences
	Earth Sciences
	Mathematics
	Oceanography, Atmospheric Sciences and Meteorology
	Physics
	Statistics and Probability
Biological and Life Science	Biochemistry, Biophysics, and Structural Biology
	Biology, Integrated Biology, Integrated Biomedical Sciences
	Cell and Developmental Biology
	Ecology and Evolutionary Biology
	Genetics and Genomics
	Immunology and Infectious Disease
	Kinesiology
	Microbiology
	Neuroscience and Neurobiology
	Nursing
	Pharmacology, Toxicology and Environmental Health
	Physiology
	Public Health
	Animal Sciences
	Entomology
	Food Science
	Forestry and Forest Sciences
	Nutrition
	Plant Sciences

4.3 The Risk and Return of Technology Transfer

We discussed a lot about risk and return of technology transfer in the above section but we haven't formulated them yet. Basically the return is the output divided by input:

$$R_{i,n} = \frac{output}{input}$$

$i-$discipline:Engineering, Physical and Mathematical Sciences, Biological and Life Sciences
$n-$year:1988,...,2008

In M3 (please see Figure 3.1), we have three inputs: federal funding, number of full-time employees in technology licensing office, and legal fee expenditure, and four outputs: number of licenses executed, licenses income received, number of start-ups initiated, or number of US patents awarded. So we could have many combinations of R. Or we could weigh all the inputs into a single input and weigh all the outputs into a single output. While these ideas are fairly intuitive, constructing a satisfactory measure of return poses an empirical challenge for a couple of reasons. First, it's very hard to determine the weights. For instance, it's hard to determine if licenses income received or the number of startups initiated is more important and by how much. It's like comparing apples with oranges. Second, the data break down by disciplines of all input and output for all universities in all years are not available. Third, the return distribution has to be Gaussian, which we will discuss further in Section 4.4. Considering all the above constraints, we use the following definition for technology transfer return, which is a mathematical formulation of Definition 1 in section 4.2.1.

$$R_{i,n} = \frac{\sum_{all\ Universities} No.\ patents_{i,n}}{\sum_{all\ Universities} Federal\ \ funding_{i,n}}$$

$i-$discipline:Engineering, Physical and Mathematical Sciences, Biological and Life Sciences
$n-$year:1988,...,2008

$$Risk = Variance(R_{i,n})$$

We get the patents data from the U.S. Patent and Trademark Office and get the federal funding data from the National Science Foundation Integrated Science and Engineering Resources Data System as shown in Figure 4.6 and Figure 4.7.

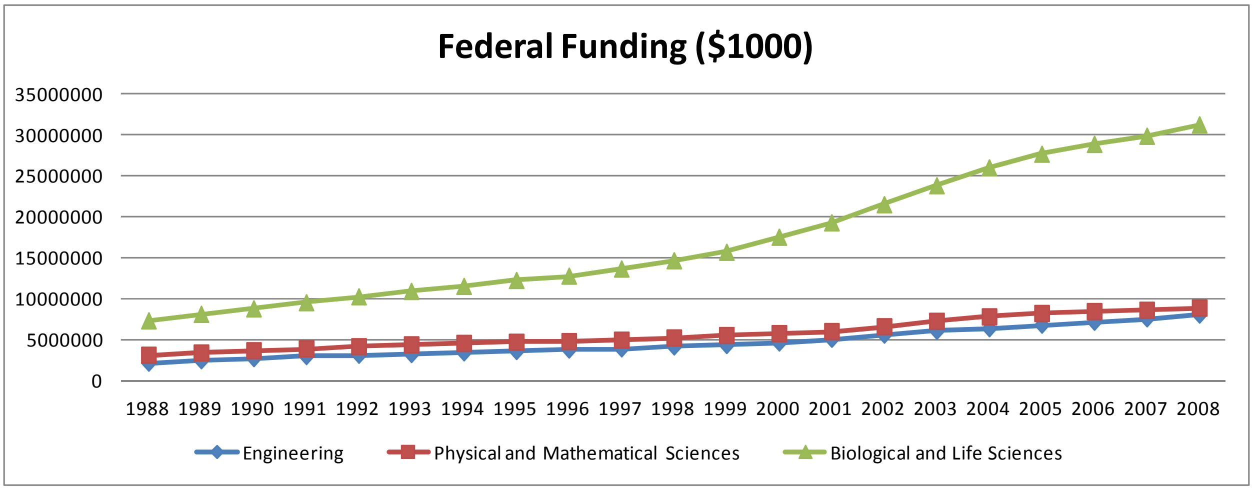


Figure 4.6: Federal funding.

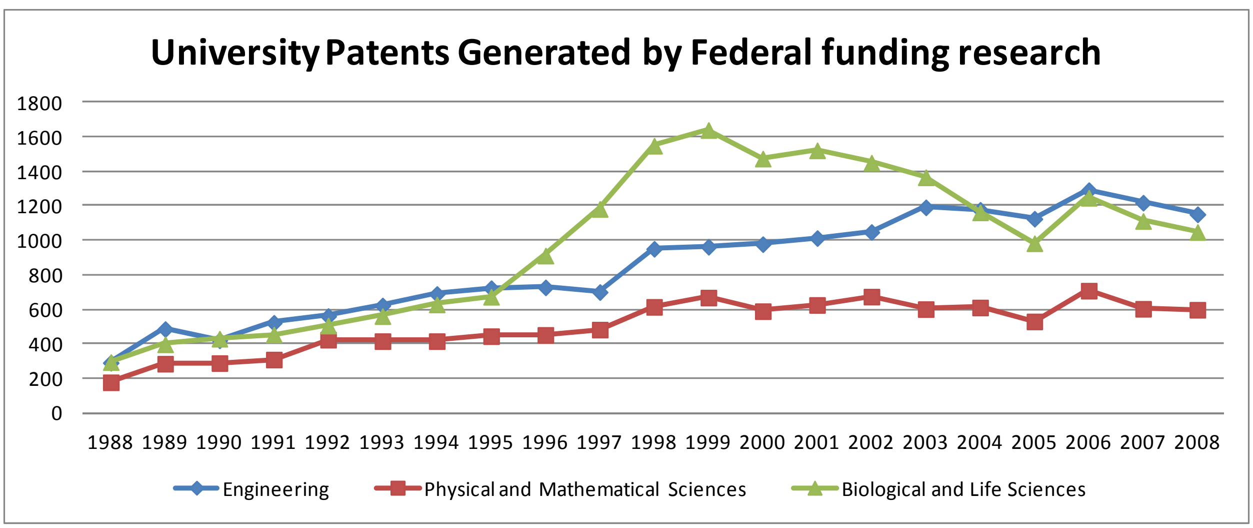


Figure 4.7: University patents generated by federal funding research.

We then categories the raw data by universities, years, and three major disciplines. These data are used to compute the time-series of the return as shown in Figure 4.8. Mean and standard deviation of return is shown in Table 4.4 and correlation matrix of three major disciplines is shown in Table 4.5. We don't see any negative correlation between these three disciplines. However, it doesn't mean we won't be able to carefully structure our research portfolio to increase return and reduce risk.

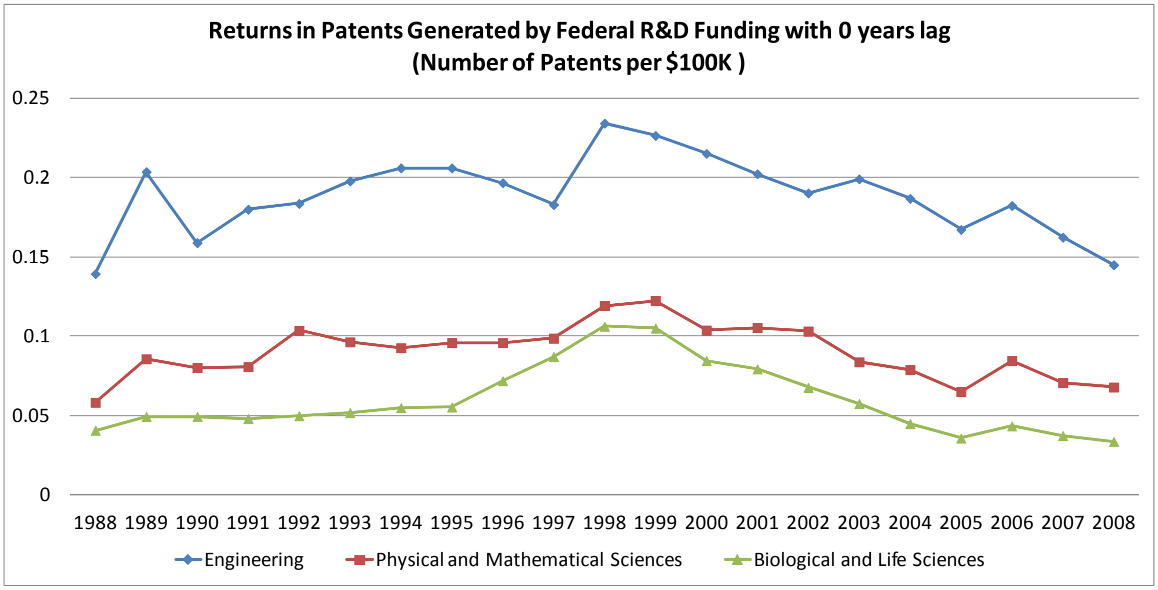


Figure 4.8: Returns in patens generated by federal research funding.

Table 4.4: Mean and standard deviation of return (0 years lag).

	Mean	Standard Deviation
Engineering	0.18878	0.02452
Physical and Mathematical Sciences	0.09013	0.01697
Biological and Life Sciences	0.05968	0.02161

Table 4.5: Correlation matrix of three major disciplines (0 years lag).

	Engineering	Physical and Mathematical Sciences	Biological and Life Sciences
Engineering	1.000000	0.858900	0.761300
Physical and Mathematical Sciences	0.858900	1.000000	0.871200
Biological and Life Sciences	0.761300	0.871200	1.000000

4. 4 Normality Test and Time Lag

One of the most important assumptions of Modern Portfolio Theory is that the return has normal distribution. So we did normality tests for the returns of Engineering, Physical and Mathematical Sciences, and Biology and Life Sciences, respectively. The results are shown in Table 4.6, Table 4.7, and Table 4.8. Engineering return follows a Normal distribution and so does physical sciences. However, biological and life sciences has a P value of 0.022 and didn't pass the normality test. Q-Q plots are drawn in Figure 4.9. It compares the theoretical normal distribution with our data distribution by plotting their quantiles against each other. The horizontal axis is the theoretical normal distribution and the vertical axis is our data. If the theoretical and real data distributions are similar, the points in the Q–Q plot will approximately lie on the line y = x. If the distributions are linearly related, the points in the Q–Q plot will approximately lie on a line, but not necessarily on the line y = x. It is seen from the figure that engineering and physical sciences Q-Q plots approximately lie on the line y = x, which indicates the data follows normal distribution. As expected, biological sciences Q-Q plot is not as beautiful as that of engineering and physical sciences because it failed the normality test.

Table 4.6: Shapiro-Wilk test of engineering (0 years lag)

Shapiro-Wilk test (Engineering 0 years lag)	
W	0.975
p-value	0.835
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.
The risk to reject the null hypothesis H0 while it is true is 83.54%.

Table 4.7: Shapiro-Wilk test of physical and mathematical sciences (0 years lag)

Shapiro-Wilk test (Physical 0 years lag)	
W	0.977
p-value	0.881
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.
The risk to reject the null hypothesis H0 while it is true is 88.14%.

Table 4.8: Shapiro-Wilk test of biological and life sciences (0 years lag)

Shapiro-Wilk test (Biological 0 years lag)	
W	0.889
p-value	0.022
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is lower than the significance level alpha=0.05, one should reject the null hypothesis H0, and accept the alternative hypothesis Ha.
The risk to reject the null hypothesis H0 while it is true is lower than 2.16%.

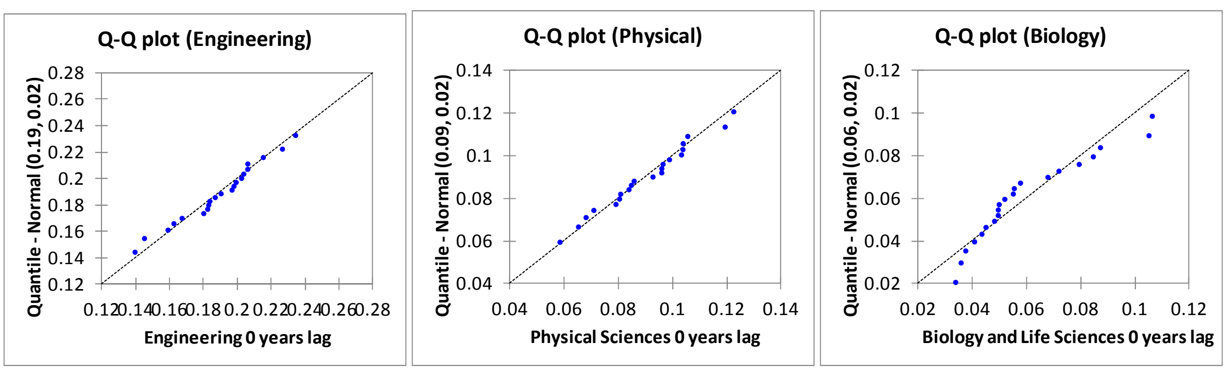


Figure 4.9: Q-Q plot of returns of engineering, physical and mathematical sciences, and biology and life sciences.

As we know, the output of technology transfer is not all generated within the year of input. There is a time lag between the federal research funding and patents generated. The range could be as short as 1 year or as long as 5 or 10 years. Some studies suggest an average of 3.5 years (Scherer and Harhoff 2000). In our research, a controlled test is performed to determine if the time lag is significant. First, we use a time lag of 3 years. The results are summarized as the following. Normality test was also performed.

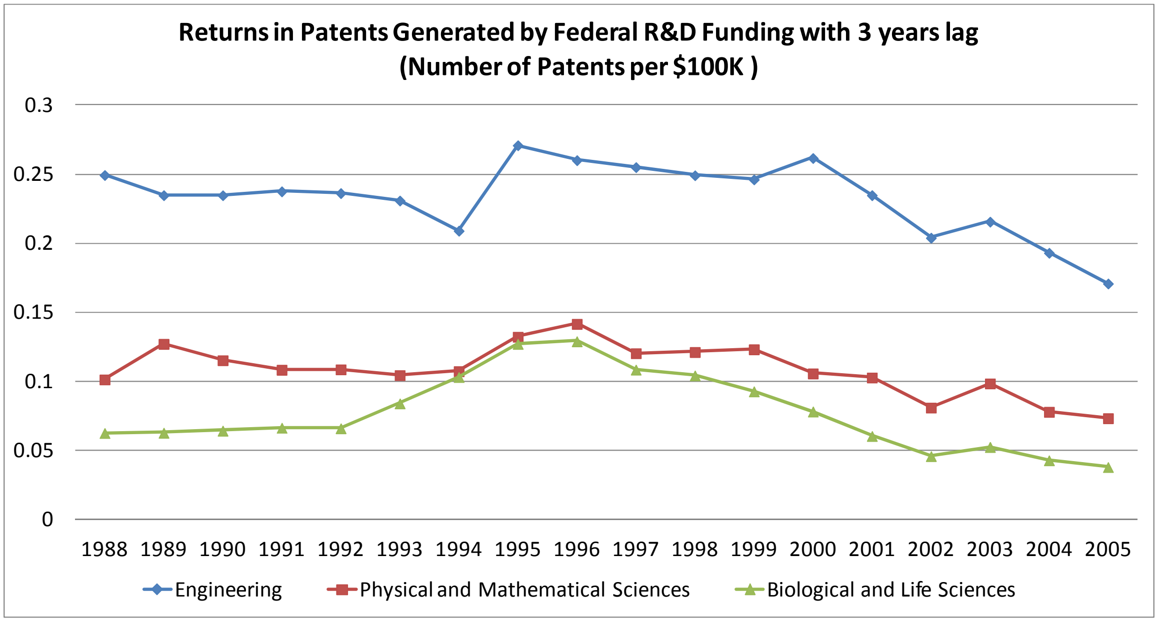


Figure 4.10: Returns in patens generated by federal research funding (3 years lag).

Table 4.9: Mean and standard deviation of return (3 years lag).

	Mean	Standard Deviation
Engineering	0.233137	0.025906
Physical and Mathematical Sciences	0.108493	0.018332
Biological and Life Sciences	0.077251	0.027952

Table 4.10: Correlation matrix of three major disciplines (3 years lag).

	Engineering	Physical and Mathematical Sciences	Biological and Life Sciences
Engineering	1.000000	0.831859	0.713074
Physical and Mathematical Sciences	0.831859	1.000000	0.823639
Biological and Life Sciences	0.713074	0.823639	1.000000

Table 4.11: Shapiro-Wilk test of engineering (3 years lag).

Shapiro-Wilk test (Engineering 3 years lag)	
W	0.940
p-value	0.286
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.
The risk to reject the null hypothesis H0 while it is true is 28.56%.

Table 4.12: Shapiro-Wilk test of physical and mathematical sciences (3 years lag).

Shapiro-Wilk test (Physical 3 years lag)	
W	0.963
p-value	0.655
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.
The risk to reject the null hypothesis H0 while it is true is 65.48%.

Table 4.13: Shapiro-Wilk test of biological and life sciences (3 years lag).

Shapiro-Wilk test (Biological 3 years lag)	
W	0.932
p-value	0.214
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H(
The risk to reject the null hypothesis H0 while it is true is 21.37%.

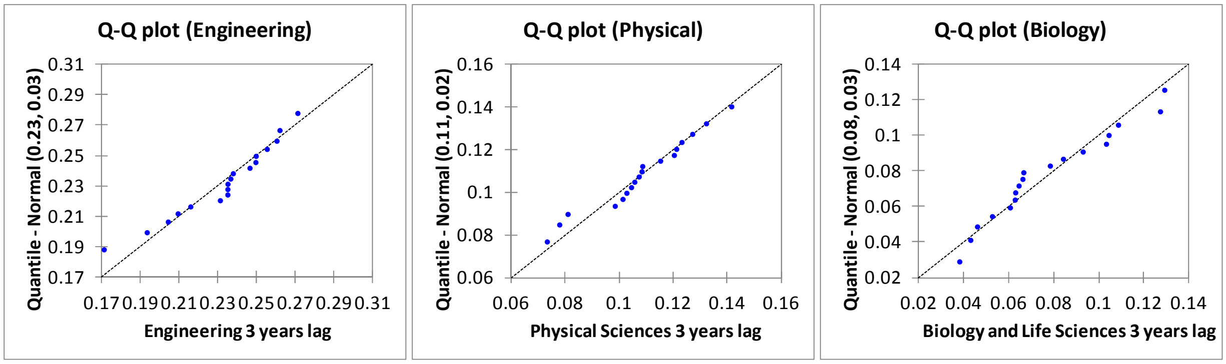


Figure 4.11: Q-Q plot of returns of engineering, physical and mathematical sciences, and biology and life sciences (3 years lag).

Then we use a time lag of 5 years to compute the patents return by federal research funding. The results are summarized as the following. Normality test was also performed.

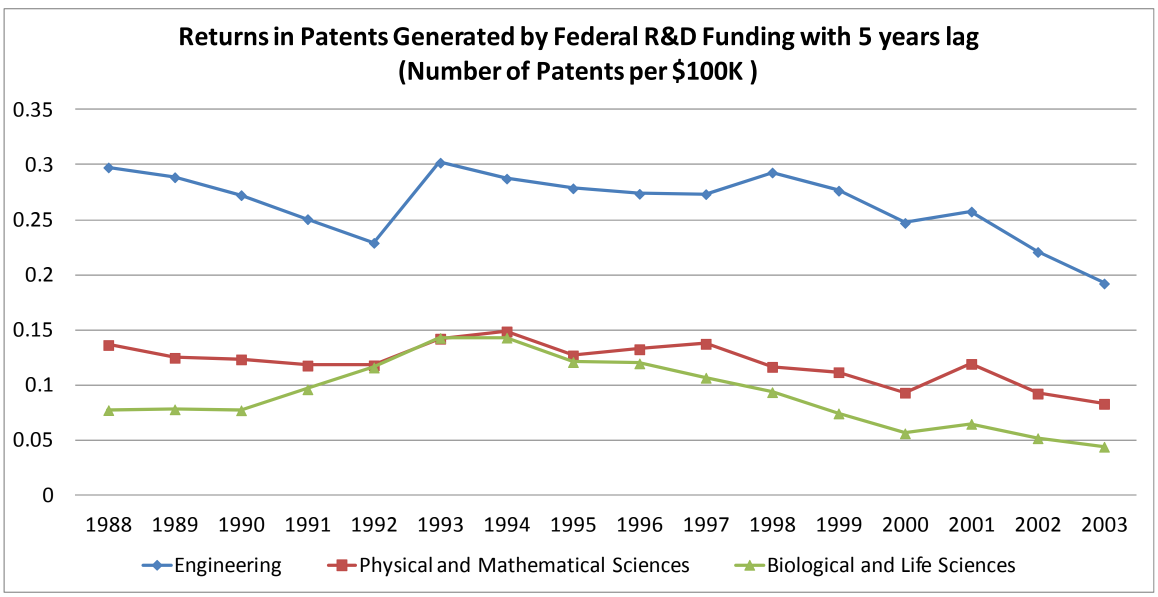


Figure 4.12: Mean and standard deviation of return (5 years lag).

Table 4.14: Mean and standard deviation of return (5 years lag).

	Mean	Standard Deviation
Engineering	0.265147	0.030435
Physical and Mathematical Sciences	0.120366	0.018383
Biological and Life Sciences	0.091552	0.031060

Table 4.15: Correlation matrix of three major disciplines (5 years lag).

	Engineering	Physical and Mathematical Sciences	Biological and Life Sciences
Engineering	1.000000	0.809003	0.555387
Physical and Mathematical Sciences	0.809003	1.000000	0.815497
Biological and Life Sciences	0.555387	0.815497	1.000000

Table 4.16: Shapiro-Wilk test of engineering (5 years lag).

Shapiro-Wilk test (Engineering 5 years lag)	
W	0.911
p-value	0.121
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.
The risk to reject the null hypothesis H0 while it is true is 12.13%.

Table 4.17: Shapiro-Wilk test of physical and mathematical sciences (5 years lag).

Shapiro-Wilk test (Physical 5 years lag)	
W	0.946
p-value	0.429
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H0.
The risk to reject the null hypothesis H0 while it is true is 42.88%.

Table 4.18: Shapiro-Wilk test of biological and life sciences (5 years lag).

Shapiro-Wilk test (Biological 5 years lag)	
W	0.952
p-value	0.519
alpha	0.05

Test interpretation:
H0: The variable from which the sample was extracted follows a Normal distribution.
Ha: The variable from which the sample was extracted does not follow a Normal distribution.
As the computed p-value is greater than the significance level alpha=0.05, one cannot reject the null hypothesis H(
The risk to reject the null hypothesis H0 while it is true is 51.90%.

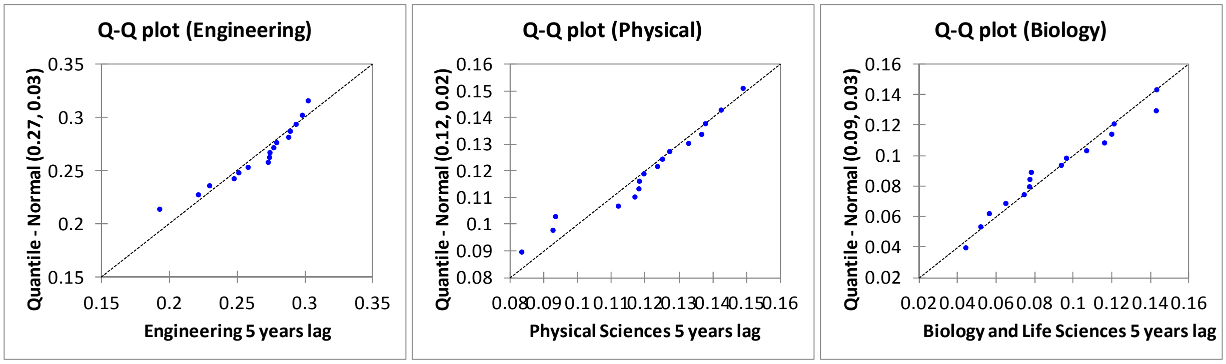


Figure 4.13: Q-Q plot of returns of engineering, physical and mathematical sciences, and biology and life sciences (5 years lag).

4.5 Research Portfolio Risk-Return Curve

From the above data analysis and normality test, it's valid to apply Modern Portfolio Theory to the return data with 3 years and 5 years lag. Since the data with 3 years lag normality test results have a little bit larger P value than that with 5 years lag, we will use the return data with 3 years lag in the following study. The risk-return curve is illustrated in the figure below by varying the combination of the three disciplines.

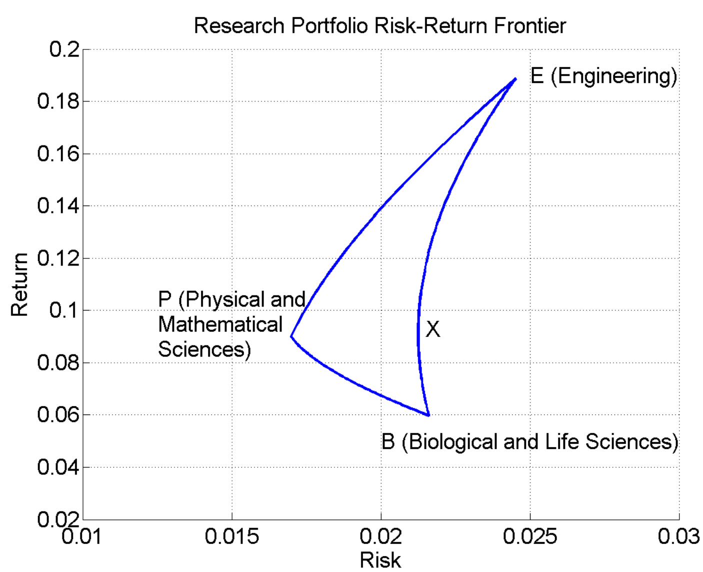


Figure 4.14: Research portfolio risk-return frontier.

Basically, every university is holding a portfolio of Engineering, Physical and Mathematical Sciences, and Biological and Life Sciences. The weight of each discipline is formulated as the following. All the universities will be within the triangle.

$$W_E = \frac{\text{Federal funding in Engineering}}{\text{Total federal funding in Engineering, Physical and Mathematical Sciences, and Biological and Life Sciences}}$$

$$W_P = \frac{\text{Federal funding in Physical and Mathematical Sciences}}{\text{Total federal funding in Engineering, Physical and Mathematical Sciences, and Biological and Life Sciences}}$$

$$W_B = \frac{\text{Federal funding in Biological and Life Sciences}}{\text{Total federal funding in Engineering, Physical and Mathematical Sciences, and Biological and Life Sciences}}$$

$$W_E + W_P + W_B = 1$$

If it's a pure medical school, like Baylor College of Medicine, then $W_B = 1$ and it will be on point B in the above figure because it doesn't hold any engineering or physical sciences research. If it's a university doesn't have any engineering research, like New York University, then $W_E = 0$ and it will be somewhere on the line connecting point P and point B. The more biological and life sciences research it has, the closer it will be to point B. Likewise, the more physical and mathematical research it has, the closer it will be to point P. For most of the other universities, like Harvard, MIT, and Stanford, they have research in all the three major disciplines and lies within the triangle. Their exact positions will be determined by their portfolio composition. The more engineering they have, the closer they will be to point E. The more physical and mathematical sciences they have, the closer they will be to point P. The more biological and life sciences they have, the closer they will be to point P. We can find some interesting features of the curve. If we move from point B to point X by adding some engineering research in the portfolio, we can increase return while reducing risk. If we move from point B to point P, anywhere on the line BP has higher return and lower risk than point B. Because point B has higher risk and lower return than point P. From the stand point of risk and return, it looks like a university shouldn't hold any biological and life sciences research in its research portfolio. But we cannot come to that conclusion because the risk and return in our model only considers the number of patents awarded. As we know from Chapter 2, there are many outputs from technology transfer and the number of patents is only one of them. Also as we know, value realized by patents is highly skewed so the number of patents only doesn't mean the value captured. A university with a blockbuster patent could result in more license fee than a university with many mediocre patents. In addition, the goal of a university is neither to maximize its number of patents awarded nor to maximize its license fee. That said, it does offer some insights in terms of risk, return and research portfolio management.

Research portfolios of the 100 Universities were computed and summarized in Table 4.18 and are illustrated in the figure below. Every dot stands for a university. It is seen that many dots are condensed near biological and life sciences, which means many universities hold heavy positions in biological and life sciences research.

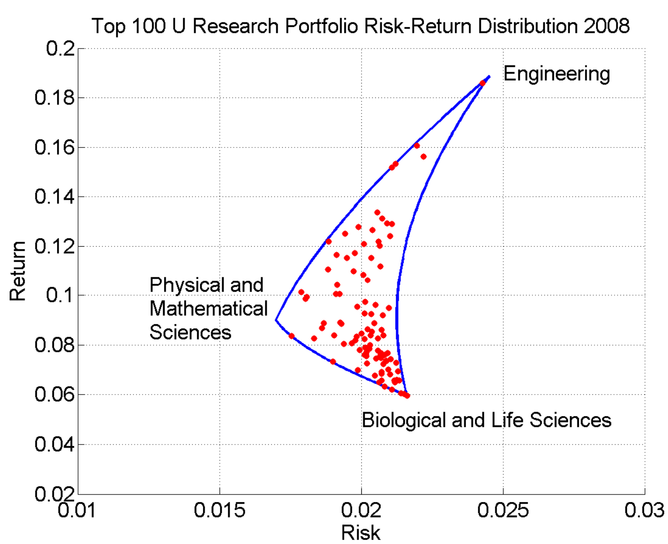


Figure 4.15: 100 University research portfolio risk-return distribution 2008.

4.6 Year to Year Research Portfolio Evolution

We are also interested in the year to year research portfolio evolution. Portfolio distribution of each year is illustrated in the following figures. It is observed that Harvard (the blue star in Figure 4.16) holds a heavy position in biological and life sciences but a very light position in engineering 1988-2002 because it almost lies on the line connecting physical sciences and biological sciences. Since 2003, it began to move towards engineering. In 2008, its engineering weight is 5.3%. Not as heavy as that of MIT and Stanford, but it increased a lot since 2004. The trend of MIT (the green circle in the figure) is opposite to Harvard. It holds a light position in biological and life sciences research 1988-2002 as it almost lies on the line connecting engineering and physical sciences. It began to add more biological and life sciences research to its portfolio from 2003 and the green circle began to move towards biological and life sciences. Stanford (black triangle in the figure) is almost in the middle of the risk-return triangle curve, which means it has a relatively balanced portfolio. It doesn't change much over the years but moved toward biological and life sciences a little bit.

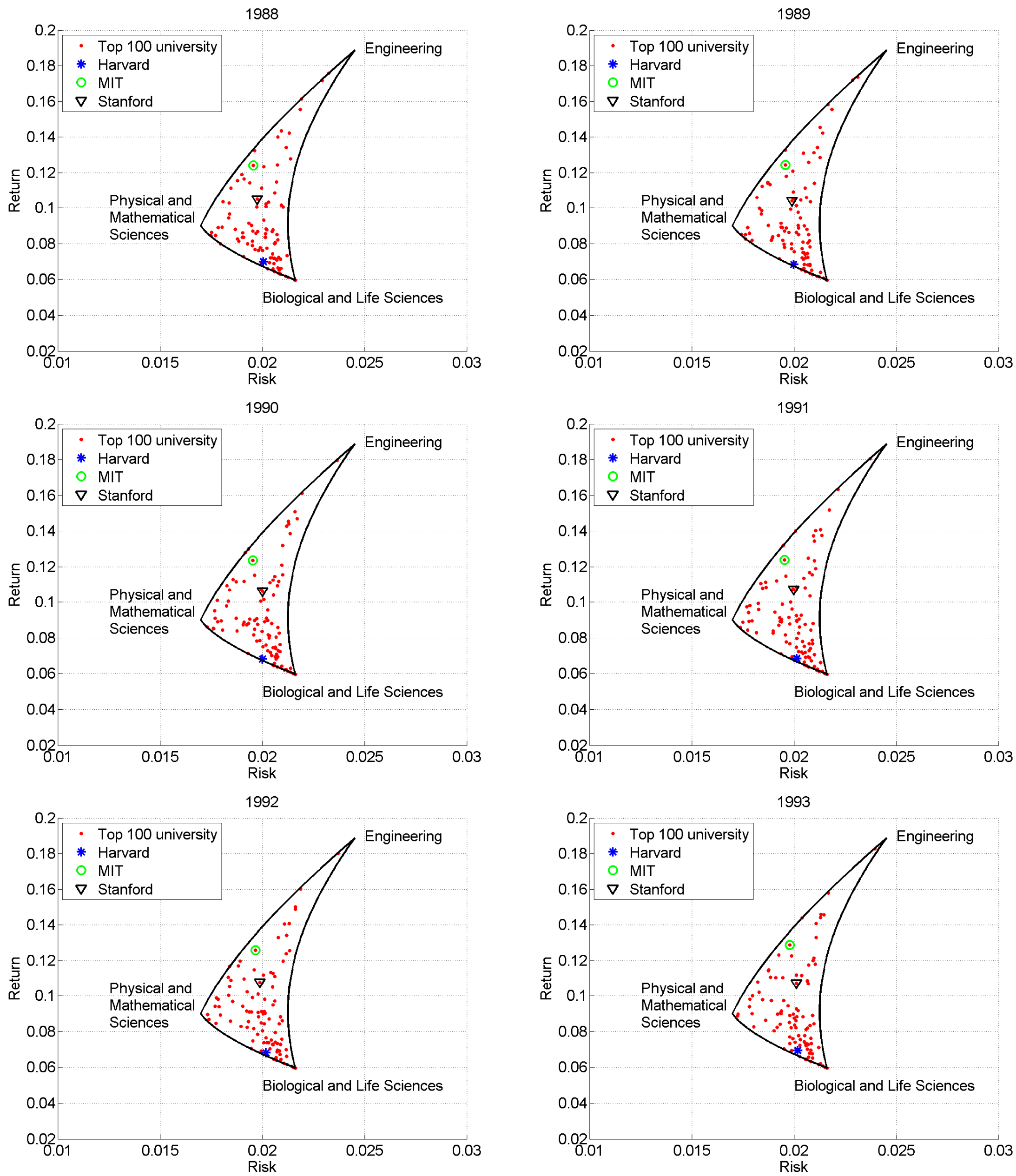


Figure 4.16: 100 university research portfolio distribution 1988-2008.

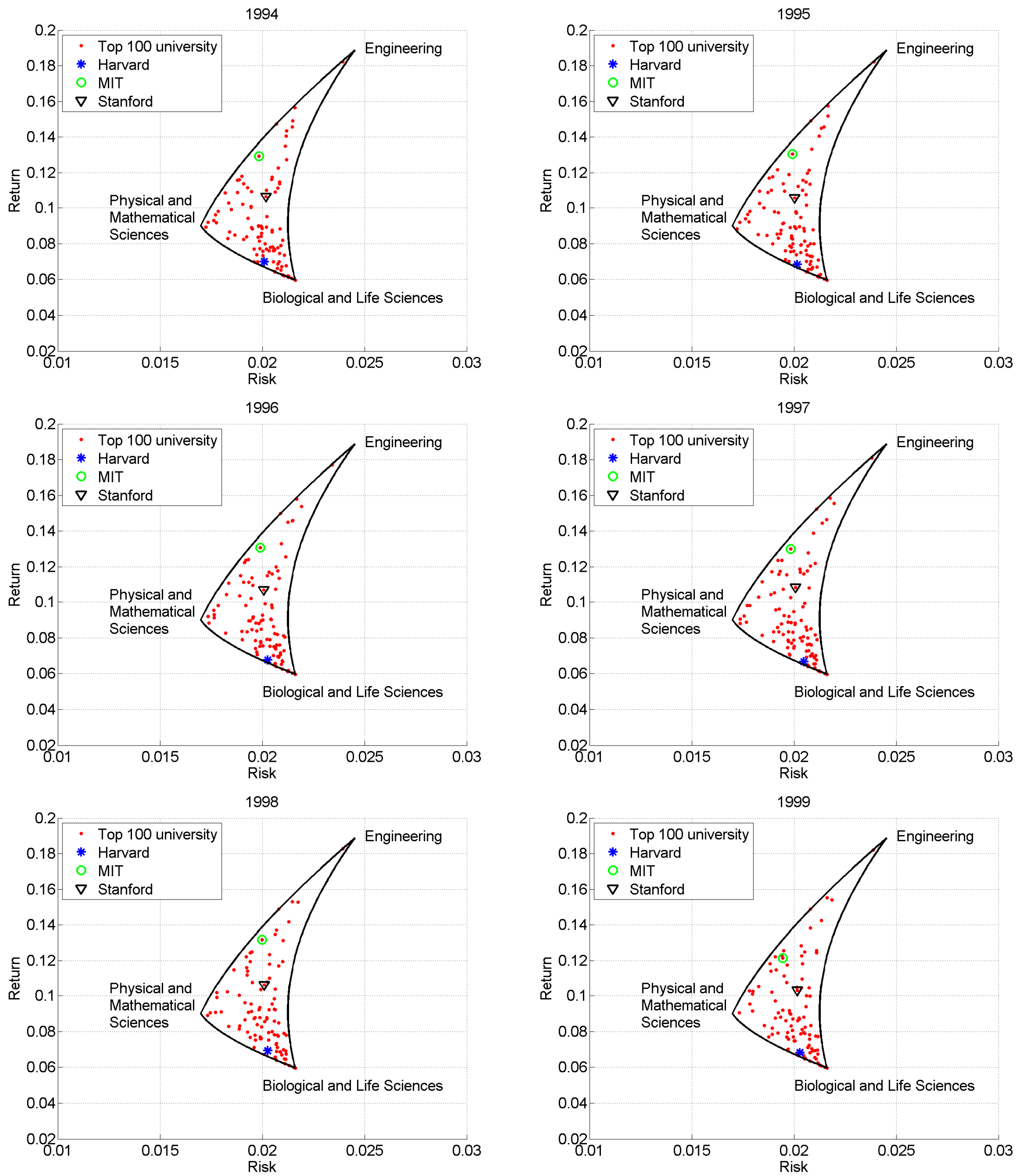


Figure 4.16 (Continued)

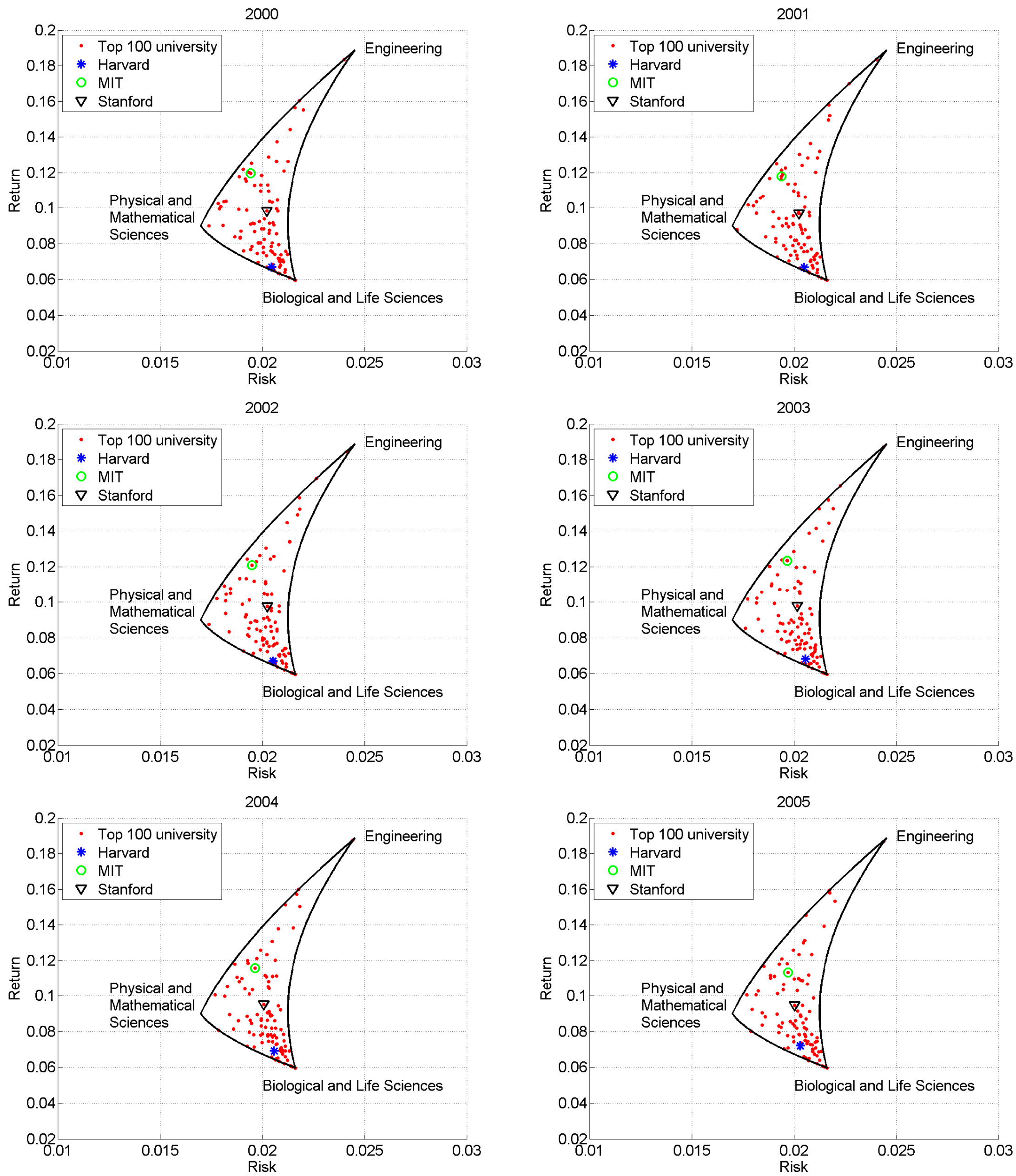


Figure 4.16 (Continued)

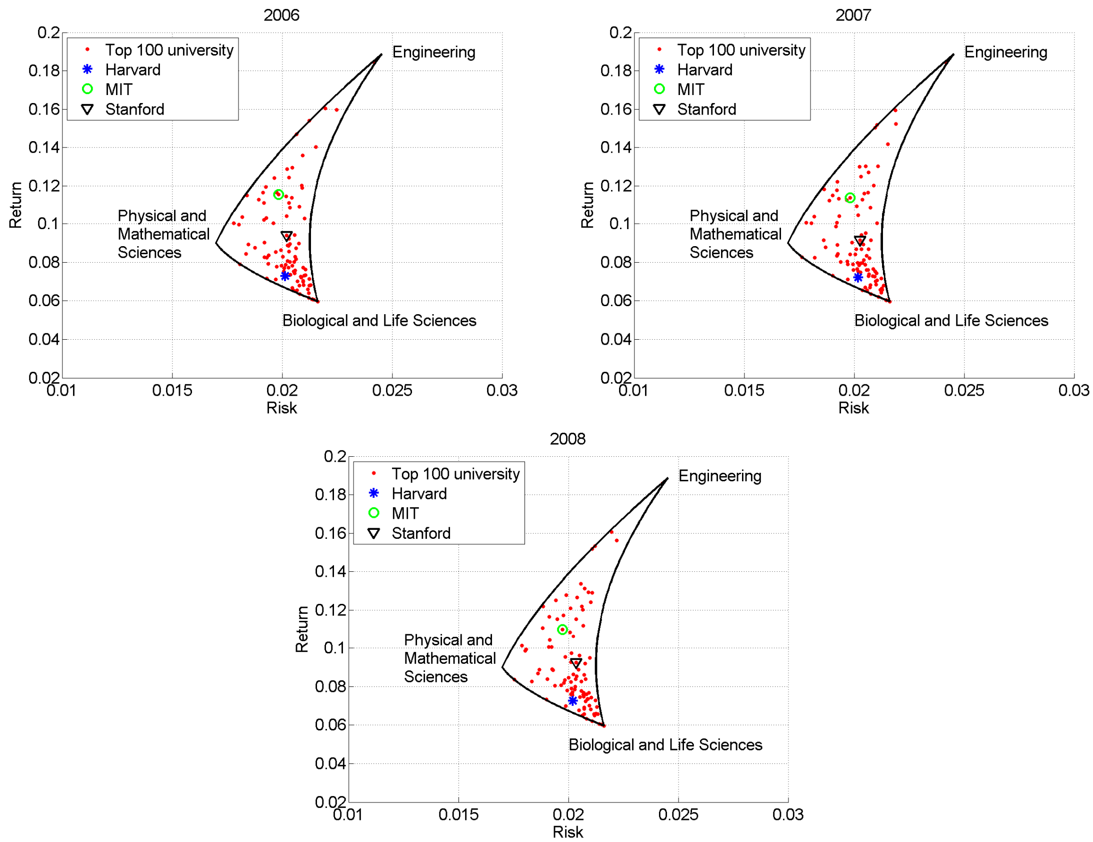


Figure 4.16 (Continued)

4.7 Correlation Between Portfolio Balance and Technology Transfer Efficiency

To address the question in the beginning of this chapter: is technology transfer efficiency correlated to university research portfolio. First, we use balance score to measure how balanced a portfolio is.

$$Balance\ Score = |W_E - \alpha_E| + |W_P - \alpha_P| + |W_B - \alpha_B|$$

$$\alpha_E + \alpha_P + \alpha_B = 1$$

Balance Score measures how far away the portfolio is from the most balanced portfolio. The most balanced portfolio is defined by the balance coefficients $(\alpha_E, \alpha_P, \alpha_B)$. Obviously its balance score is 0. Then we run regressions to study the relationship between Balance Score and technology transfer efficiency. The smaller the balance score, the more balanced the portfolio is. The larger the technology transfer efficiency, the more efficient so we use inverse efficiency in our regression. So we run regressions of balance score with inverse efficiency.

$$Inverse\ efficiency = 1 / Efficiency$$

We use a simple search algorithm to find the balance coefficients $(\alpha_E, \alpha_P, \alpha_B)$. For the three-dimension simplex given by $\alpha_E + \alpha_P + \alpha_B = 1$, we discretize the simplex at the precision of 0.01, and we first generate the sets of balance scores for each point on the discretized simplex. At each point, we regress the inverse efficiency on the corresponding balance score, and save the t-statistic for the regression coefficient. As a higher t-statistic implies a more significant correlation between the inverse efficiency and the balance score, we sort all t-statistics and find the largest t-statistic, whose associated optimal balance coefficients are optimal. Following this algorithm, the global optimal balance coefficients are given by (0.46, 0.42, 0.12). We also show that the discretization we use is precise enough by considering perturbations at the neighborhood of the optimal balance coefficients. Figure 4.17 shows the t stat for different combinations of α_E and α_P. Note that $\alpha_B = 1 - \alpha_E - \alpha_P$, so there are only two dimensions of freedom. The maximum t stat is 4.78 when $(\alpha_E, \alpha_P, \alpha_B) = (0.46, 0.42, 0.12)$.

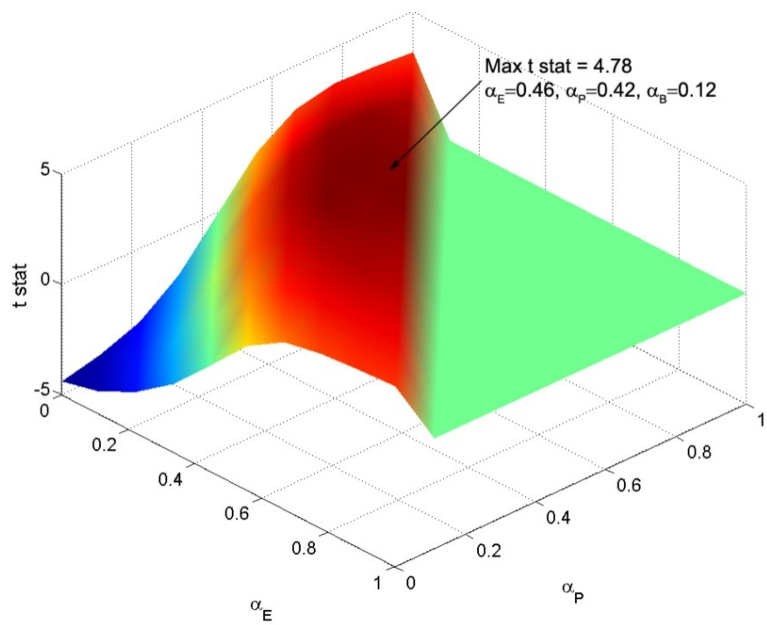


Figure 4.17: Find the balance coefficients.

Now insert the balance coefficients into the balance score formula, we get

$$Balance\ Score = |W_E - 0.46| + |W_P - 0.42| + |W_B - 0.12|$$

Then efficiency scores of the 100 Universities were calculated and the results are summarized in the following table.

Table 4.19: Technology transfer efficiency and research portfolio balance score.

University	EFF	WE	WP	WB	BS
Arizona State University	0.3957	0.3602	0.3588	0.2809	0.3219
Auburn University	0.5846	0.5036	0.1424	0.3540	0.5552
Baylor College of Medicine	0.6311	0.0000	0.0000	1.0000	1.7600
Boston University	0.8830	0.1152	0.1739	0.7110	1.1820
Brigham Young University	1.0000	0.4017	0.3097	0.2886	0.3371
California Institute of Technology	1.0000	0.1385	0.6928	0.1686	0.6429
Carnegie Mellon University	0.9635	0.3300	0.6439	0.0261	0.4477
Case Western Reserve University	0.2960	0.0952	0.0253	0.8795	1.5191
Clemson University	1.0000	0.4963	0.1816	0.3221	0.4768
Colorado State University	0.7913	0.0897	0.5140	0.3963	0.7406
Columbia University	0.6382	0.0764	0.2156	0.7081	1.1762
Cornell University	0.6057	0.1398	0.2271	0.6331	1.0262
Dartmouth College	0.5608	0.1061	0.0889	0.8050	1.3700
Duke University	0.6681	0.0624	0.0769	0.8607	1.4815
East Carolina University	0.6821	0.0152	0.1324	0.8524	1.4649
Emory University	0.2384	0.0400	0.0265	0.9335	1.6271
Florida State University	0.8074	0.2644	0.5492	0.1864	0.3912
Georgetown University	0.4709	0.0000	0.0315	0.9685	1.6970
Georgia Institute of Technology	1.0000	0.7235	0.2465	0.0300	0.5271
Harvard University	0.6594	0.0529	0.2035	0.7436	1.2472
Indiana University	0.3011	0.0230	0.1663	0.8107	1.3814
Iowa State University	0.8086	0.3097	0.2110	0.4794	0.7187
Johns Hopkins University	0.8134	0.4260	0.1839	0.3902	0.5403
Kansas State University	0.7085	0.2070	0.2080	0.5850	0.9301
Kent State University	1.0000	0.0006	0.7828	0.2166	0.9188
Massachusetts Inst. of Technolog	1.0000	0.3114	0.3316	0.3570	0.4739
Michigan State University	1.0000	0.1084	0.2684	0.6232	1.0064
Michigan Technological University	0.7382	0.6275	0.3630	0.0095	0.3351
Mississippi State University	1.0000	0.4343	0.1993	0.3663	0.4927
Montana State University	1.0000	0.2156	0.2630	0.5215	0.8029
New Jersey Institute of Technolog	1.0000	0.6416	0.3549	0.0035	0.3631
New Mexico State University	1.0000	0.7172	0.1310	0.1517	0.5779
New York University	0.7597	0.0000	0.1209	0.8791	1.5181
North Carolina State University	0.8349	0.3178	0.2489	0.4333	0.6266
North Dakota State University	1.0000	0.2424	0.4385	0.3190	0.4351
Northwestern University	1.0000	0.1819	0.0946	0.7235	1.2071
Ohio State University	0.4229	0.1607	0.1593	0.6799	1.1199
Ohio University	1.0000	0.4981	0.2351	0.2668	0.3697
Oklahoma State University	0.4782	0.3705	0.1396	0.4899	0.7398
Oregon Health Sciences Universit	0.5074	0.0000	0.0813	0.9187	1.5973
Oregon State University	0.4501	0.1389	0.3762	0.4849	0.7298
Penn State University	0.9284	0.4526	0.2779	0.2694	0.2989
Purdue University	0.8460	0.3782	0.2198	0.4020	0.5640
Rice University	1.0000	0.3864	0.5075	0.1062	0.1750
Rutgers	1.0000	0.1364	0.3682	0.4954	0.7507
Stanford University	1.0000	0.2159	0.1639	0.6202	1.0004
State University of New York	0.7928	0.0745	0.2021	0.7235	1.2069
Temple University	0.3273	0.0441	0.1231	0.8328	1.4257
Texas A&M University System	0.5978	0.2146	0.4311	0.3544	0.4909
Tufts University	0.2837	0.0877	0.0804	0.8319	1.4237
Tulane University	0.2507	0.0384	0.0395	0.9221	1.6041
Univ. of Akron	1.0000	0.4320	0.4070	0.1610	0.0820
Univ. of Arizona	0.8884	0.0897	0.4182	0.4920	0.7441
Univ. of Arkansas	0.3510	0.0896	0.1132	0.7972	1.3544
Univ. of California System	1.0000	0.0805	0.2042	0.7153	1.1906
Univ. of Cincinnati	0.5962	0.0695	0.0209	0.9096	1.5791
Univ. of Colorado	1.0000	0.0788	0.3487	0.5724	0.9049
Univ. of Connecticut	0.9028	0.1094	0.1253	0.7654	1.2907
Univ. of Dayton Research Institute	0.5262	0.9735	0.0154	0.0111	1.0270
Univ. of Delaware	1.0000	0.5041	0.2955	0.2004	0.2491
Univ. of Florida	0.8542	0.1917	0.1418	0.6666	1.0932
Univ. of Georgia	1.0000	0.0382	0.1239	0.8379	1.4358
Univ. of Hawaii	0.9552	0.0430	0.5763	0.3808	0.8341
Univ. of Idaho	0.2083	0.2486	0.1394	0.6120	0.9840
Univ. of Illinois Urbana Champaigr	0.7176	0.3332	0.4111	0.2557	0.2714
Univ. of Iowa	0.3557	0.0867	0.0859	0.8274	1.4148
Univ. of Kansas	0.2747	0.0824	0.1417	0.7759	1.3118
Univ. of Kentucky	1.0000	0.1675	0.0868	0.7458	1.2516
Univ. of Louisville	0.3889	0.1173	0.0674	0.8153	1.3907
Univ. of Maryland Baltimore	0.3593	0.0000	0.0000	1.0000	1.7600
Univ. of Maryland College Park	1.0000	0.3181	0.5144	0.1675	0.2838
Univ. of Massachusetts	0.3677	0.1440	0.7602	0.0958	0.6805
Univ. of Miami	0.1585	0.0155	0.2693	0.7152	1.1904
Univ. of Michigan	0.9838	0.2292	0.0867	0.6841	1.1282
Univ. of Minnesota	0.6464	0.1052	0.1108	0.7840	1.3280
Univ. of Nebraska	0.5300	0.1478	0.1679	0.6843	1.1287
Univ. of New Hampshire	0.6764	0.1451	0.6851	0.1698	0.6298
Univ. of New Mexico	0.7495	0.1263	0.2069	0.6669	1.0937
Univ. of North Carolina	0.5586	0.0065	0.1479	0.8456	1.4512
Univ. of Oklahoma	0.5977	0.0849	0.2441	0.6709	1.1019
Univ. of Oregon	0.4614	0.0026	0.4358	0.5616	0.9148
Univ. of Pennsylvania	0.4791	0.0497	0.0710	0.8794	1.5187
Univ. of Pittsburgh	0.5456	0.0337	0.0536	0.9128	1.5856
Univ. of Rhode Island	1.0000	0.1083	0.4993	0.3924	0.7033
Univ. of Rochester	0.4790	0.2601	0.0502	0.6897	1.1394
Univ. of South Alabama	1.0000	0.0877	0.2005	0.7118	1.1837
Univ. of South Carolina	0.8018	0.2208	0.4043	0.3749	0.5098
Univ. of South Florida	1.0000	0.0973	0.1141	0.7886	1.3373
Univ. of Southern California	0.7648	0.0936	0.2923	0.6142	0.9883
Univ. of Tennessee	0.4934	0.2423	0.2080	0.5497	0.8593
Univ. of Utah	1.0000	0.1035	0.1794	0.7170	1.1941
Univ. of Virginia	0.4574	0.1488	0.1192	0.7319	1.2238
Univ. of Washington	1.0000	0.1009	0.2055	0.6937	1.1473
Univ. of Wisconsin-Madison	0.7483	0.1224	0.2571	0.6204	1.0009
Vanderbilt University	0.4638	0.0993	0.0562	0.8445	1.4490
Virginia Tech	1.0000	0.4694	0.1285	0.4022	0.5831
Wake Forest University	0.4304	0.0000	0.0171	0.9829	1.7259
Washington State University	0.4787	0.1635	0.1847	0.6518	1.0636
Washington University	1.0000	0.0294	0.0513	0.9193	1.5986
Wayne State University	0.2955	0.0000	0.0000	1.0000	1.7600

Note:
EFF: M3 Technology Transfer Efficiency
WE: Weight of Engineering
WP: Weight of Physical and Mathematical Sciences
WB: Weight of Biological and Life Sciences
BS: Balance Score
2008 Data

Then we did a regression of balance score with inverse efficiency as shown in the following table and figure.

Table 4.20: Regression of balance score and inverse efficiency.

Regression Statistics	
Multiple R	0.434571409
R Square	0.188852309
Adjusted R Square	0.180575292
Standard Error	0.861292857
Observations	100

Analysis of variance					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	16.92583603	16.92583603	22.81646918	6.25238E-06
Residual	98	72.69888771	0.741825385		
Total	99	89.62472375			

T test						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.776003777	0.213690825	3.631432362	0.00045052	0.351941301	1.200066254
Coeff	0.938949603	0.196570374	4.776658789	6.25238E-06	0.548862104	1.329037102

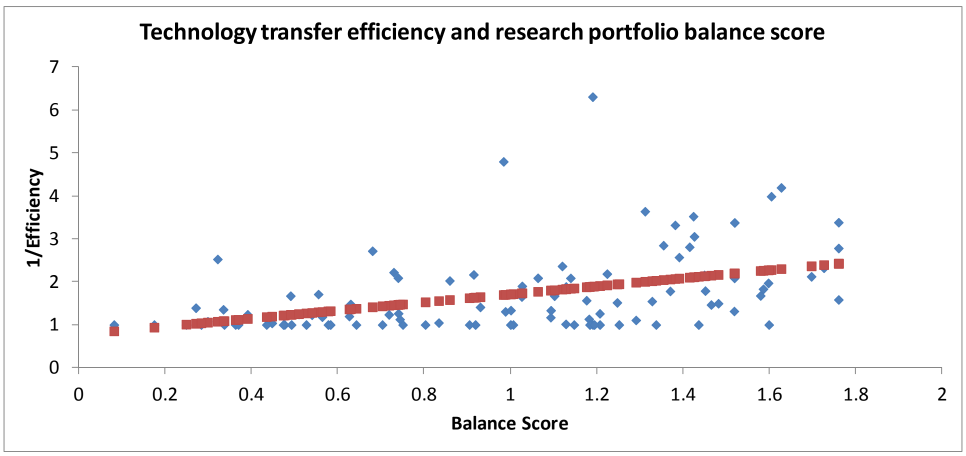


Figure 4.18: Technology transfer efficiency and research portfolio balance score (2008).

Then 100 universities portfolios are drawn in Figure 4.18. The virtual optimal portfolio is also drawn. It is observed that MIT is closer to the optimal portfolio than Stanford and Harvard.

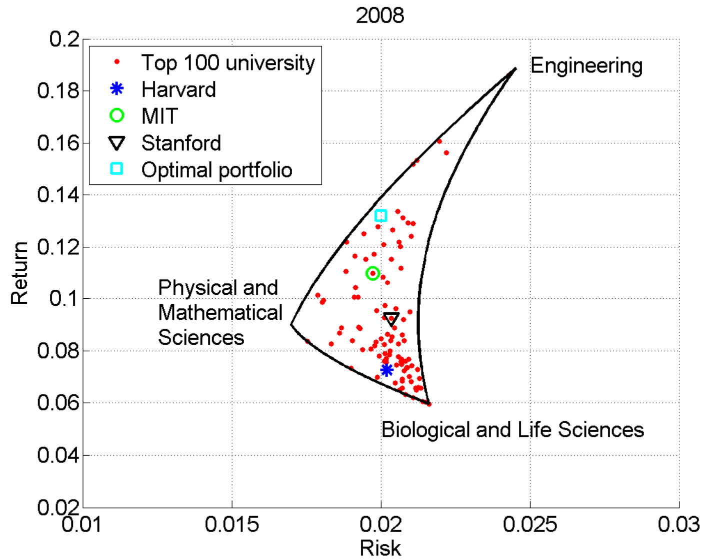


Figure 4.19: The optimal portfolio.

From the above study, we conclude that a balanced research portfolio is correlated to technology transfer efficiency. The more balanced a University's research portfolio, statistically the more efficient is its technology transfer.

Chapter 5 Conclusions

5.1 Summary of Contributions

My dissertation makes a number of contributions. Chapter 2 offers a better understanding of the industry by providing detailed analysis of U.S. Universities licensing activities. It contributes to the empirical literature in this subject.

In Chapter 3, a two-stage technology transfer model based on Data Envelopment Analysis is proposed to address limitation of a single-stage model (Thursby and Kemp 2002). The two-stage model can evaluate the efficiencies of university research and technology transfer office separately and also as a whole, offering better insights for university technology transfer management. Year to year productivity changes are also measured using Malmquist Index. It is found the productivity growth has stemmed primarily from a growth in commercialization by all universities rather than a catching up by the inefficient universities. Finally, technology transfer efficiency and academic reputation is studied for the first time. Counter intuitively, they are not correlated.

Chapter 4 opens the possibility of University research portfolio management and offers a new perspective for University management by creatively applying Modern Portfolio Theory to University research portfolio management and technology transfer for the first time. Modern Portfolio Theory makes its way in the literature of technology transfer. Three disciplines model and risk-return curves were derived. It is found a balanced portfolio is correlated to technology transfer efficiency.

5.2 Future Research

There are several ways to extend this research. In Chapter 2, there are actually more than 8 inputs and outputs in the two-stage university technology transfer model. The model can be further extended to include industrial funding. Chapter 4 shed light on a whole new direction of research, i.e. using Modern Portfolio Theory to study University research portfolio management. I only studied the number of patents and federal funding. There are actually more inputs and outputs and the model can be further developed to include more variables. It will offer a whole new perspective in University research portfolio management.

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